

ARTIFICIAL INTELLIGENCE AS A SOCIAL INNOVATION FOR
ADVANCING SUSTAINABLE FINANCE DURING THE COVID-19
PANDEMIC

by
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STATEMENT OF CONTRIBUTIONS

I am the sole author of Chapter 1 and 5 of this dissertation. Chapters 2-4 are based on academic work and papers that were co-authored with other scholars and academic contributors. Chapter 2 was based on a book chapter co-authored with Olaf Weber and I was the lead author on this paper. Chapter 3 and 4 were co-authored with Zachary Folger-Laronde, Leah Feor, and Olaf Weber, and I was the lead author on these papers. Bibliographic citations for the paper and the co-authored chapters are based on below:

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Chapter 4: Economic stimulus or ESG: What helped ‘immunize’ firms from COVID-induced market volatility?

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ABSTRACT

Social innovations have played an increasingly prominent role in responding to climate change and systemic crises such as the COVID-19 pandemic. Among these, artificial intelligence (AI) has emerged within the field of sustainable finance, offering novel capabilities for deriving insights, informing decisions, and addressing complex socio-ecological concerns. This dissertation explores whether and how AI, as a social innovation, can contribute meaningfully to sustainable development. Grounded in social innovation theory, this research critically examines both the promise and limitations of AI in addressing the sustainable development goals (SDGs). In parallel, this dissertation engages with environment, social, governance (ESG) practices as an adjacent social innovation, deeply institutionalized but often constrained in their responsiveness to crisis. Through a comparative and critical analysis, this dissertation explores how AI intersects with ESG in supporting firm-level resilience, assessing their respective and combined capacities to support firms navigate periods of crisis. Findings reveal that during the COVID-19 pandemic, AI-generated public sentiment data more strongly correlated with financial returns and market volatility during this crisis than conventional ESG ratings. Moreover, financial interventions (e.g., economic stimulus) proved more effective in stabilizing firm performance than ESG performance. By advancing the theoretical understanding of AI and ESG as distinct yet interreacting social innovations, this research offers new insights into their strategic roles in enhancing organizational resilience and promoting sustainable development. It contributes both academically and practically, bridging sustainability management with emerging technologies, and laying the foundation for future scholarship in a field increasingly shaped by complexity, uncertainty, and techno-solutionist narratives.

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LIST OF ACRONYMS

Artificial Intelligence	AI
Bank of Canada	BoC
Capital Asset Pricing Model	CAPM
Coronavirus Aid, Relief, and Economic Security	CARES
Carbon Dioxide	CO ₂
Coronavirus Disease 2019	COVID-19
Environmental, Social and Governance	ESG
Financial Technology	Fintech
Financial Stability Board	FSB
Generative AI	GenAI
Group of Twenty	G20
Global Financial Crisis	GFC
Global Partnership for Financial Inclusion	GPFI
Information And Communications Technology	ICT
International Monetary Fund	IMF
International Telecommunication Union	ITU
Large Language Models	LLMs
Non-Governmental Organizations	NGOs
Natural Language Processing	NLP
Organisation for Economic Co-operation and Development	OECD
Ordinary Least Squares	OLS
Quarter One, Two	Q1, 2
Sustainability Accounting Standards Board's	SASB
Sustainable Development Goals	SDGs
Small And Medium-Sized Enterprises	SMEs
Socially Responsible Investing	SRI
Truvalue Labs	TVL

1. INTRODUCTION

Humanity is still in the foothills of the digital age. The peaks are yet uncharted, and their promise still untold.

-UN Secretary-General's High-level Panel on Digital Cooperation (2019)

The utilization of artificial intelligence (AI) within the finance field has permeated our global society, with the COVID-19 pandemic in 2020 further amplifying its magnitude and implications (Pashang & Weber, 2021). The adoption of such financial technology (fintech) applications has been increasingly employed over the past several years to address the sustainable development goals (SDGs) at the institution and societal levels (Carè et al., 2024). This research adopts the term “AI for sustainable finance” to encompass the utilization of such fintech applications in addressing sustainability (Pashang & Weber, 2023, p. 204).

Fintech developments can be broadly categorized into two primary approaches: institutional and societal. Institutional AI for sustainable finance is predominantly used by investors and stakeholders to integrate environmental, social and governance (ESG) insights into capital allocation, risk assessment, and decision-making. In contrast, societal AI for sustainable finance is focused on enhancing financial inclusion by providing financial services to underbanked and unbanked individuals (Pashang & Weber, 2021). Although there is some overlap between these two vantage points, distinguishing between them is necessary for understanding their distinct implications in sustainable finance.

Following the aftermath of the 2008 global financial crash (GFC), fintech emerged as a response to address gaps in the formal banking sector, such as the need for alternative lending platforms, real-time payment networks and investment services, while also modernizing the

delivery of financial services through automation, increased efficiency, and digital innovation. This early fintech wave included the digitization of lending and underwriting processes, the automation of trading and settlement systems, and the streamlining of back-office operations in banking (Cortina & Schmukler, 2018). Since 2018, fintech has since witnessed rapid growth, expanding beyond early adopters to become a widely adopted commercial and mainstream service offering (Statista, 2025). The Financial Stability Board (FSB) provides a comprehensive definition of fintech as a “technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services” (FSB, 2021 para. 1). Put simply, fintech includes digital innovations used for financial services.

While the initial evolution of fintech was driven by start-ups addressing gaps in intermediation left by traditional banking institutions (Aaron et al., 2017), the landscape has expanded to include start-ups, challenger digital banks, government agencies, and incumbent banks. These entities now utilize various subsets of AI, such as machine learning, natural language processing (NLP), and deep learning, to address socially responsible investing (SRI) and enhance financial inclusion - in hopes of progressing the 17 sustainable development goals (SDGs) approved by the United Nations (UN) (Pashang & Weber, 2023).

However, despite the growing body of literature on fintech and its relationship with formal financial systems on a global and regional scale, there remains a pressing need to identify and understand the implications of AI for sustainable finance across institutional and societal applications. The scarcity of studies and the absence of agreed-upon measures in this domain could contribute to potential fragmentation in future outcomes. On the one hand, AI for

sustainable finance has been shown to enable efficiencies for various stakeholders and industries, while on the other, it has been shown to inhibit progress toward sustainable development by presenting new or existing unintended consequences.

To bring together a coherent conceptualization of AI for sustainable finance, and to address an existing gap in the literature, we define AI for sustainable finance as: AI-based social innovations used in societal or institutional-level sustainable finance initiatives. Given that social innovations are often evaluated based on their durability, scale, and systemic impact (Westley, 2014), the extent to which AI and ESG can be considered true innovations remains an open question. This research is guided by social innovation theory (Cajaiba-Santana, 2014; Mulgan et al., 2007; Westley et al., 2006; Westley & Antadze, 2010) to allow for more sound analyses of AI for sustainable finance. The research relies on quantitative methods in which data was drawn from secondary data. This research contributes to the existing knowledge through its methodological exploration in determining which practices and learnings from these interactions can be applied to initiatives utilizing AI for sustainable finance.

1.1 Background

Today, the impacts of climate change are undoubtedly present. Every year, climate-related factors take the lives of about 13 million people, and between 2000-2019, direct losses from climate change cost an estimated \$2.8 trillion (Newman & Noy, 2023; UN, n.d.-a). Scientists, practitioners, and scholars have made crucial discoveries and produced seminal literature (e.g., Collins et al., 2013; Griggs et al., 2013; Houghton et al., 1990; IPCC, 2021; Weber et al., 2010) to bridge the divide and to mitigate permanent climate changes, yet commitments by leaders at the global stage (e.g., COP28) thus far have fallen short. Indeed,

politicians and corporations have come under scrutiny due to the increased anthropogenic pressures they inflict on our biosphere (IPCC, 2019, 2021). To address such global concerns, in 2015, the UN introduced 17 SDGs to mobilize multi-stakeholder programs that reduce social, environmental, and economic challenges by 2030 (UN, 2019d). Figure 1-1 illustrates these seventeen goals. In response, some stakeholders belonging to non-profit, public, and private sectors are independently or in partnership answering the call and trying to define themselves against the goals (Mintzberg, 2015). Some in the global community have turned to social innovations, specifically AI, to help understand, improve, or mitigate such challenges (UN, 2019b).

Figure 1-1 The Sustainable Development Goals

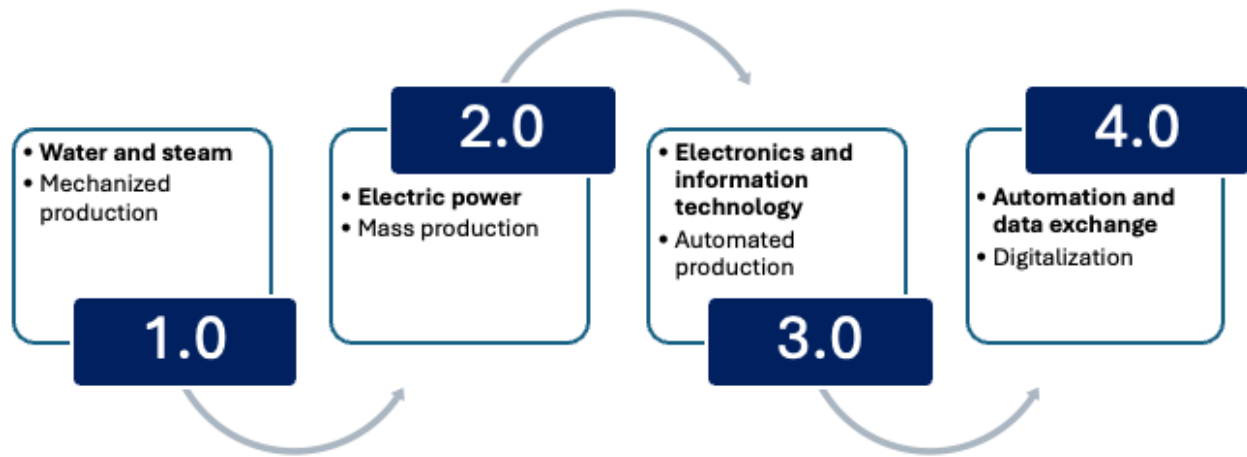


Note. From “Sustainable Development Goals kick off with start of new year”, (UN, 2015) <https://www.un.org/sustainabledevelopment/blog/2015/12/sustainable-development-goals-kick-off-with-start-of-new-year/>

One of the earliest predictions of climate change was made by Nobel laureate Svante Arrhenius in 1896 when he theorized that CO₂ release caused by human activity would warm the

earth by 5°C (Rodhe et al., 1997). The science behind Arrhenius' prediction has not changed much, but emergent technologies have created opportunities to predict and model climate changes in a significantly more sophisticated way (Rolnick et al., 2019). From the 1900s-1950s tabulating systems were created to streamline accounting and inventory tracking (Pashang & Weber, 2023). Between the 1950s-2000s, these systems expanded to programmable ones, where calculations could be achieved. By the 2010-2020s, technology had advanced to cognitive systems, integrating machine learning, NLP, and big data analysis (Truvalue Labs, 2019). This era is often described as the Fourth Industrial Revolution, signifying a significant advancement in innovation (IGEL, 2014; ITU, 2019a). Figure 1-2: Industrial Revolutions (ITU, 2017, p. 36) shows that in less than 200 years, humans have advanced from creating steam and water-powered machines that replace tedious and intensive human labour, to developing tools and devices that can learn from and communicate with one another and humans. In only a few years, technology evolved from historical data analysis, real-time information, and predictive modelling (ITU, 2018). Recently, multimodal large language models (LLMs) have been used by firms such as OpenAI to develop generative pre-trained transformers (GPTs) services such as ChatGPT (OpenAI, 2023). While financial institutions such as Morgan Stanley, Stripe, and Bloomberg have been early adopters of such AI systems, it is unclear how the so called 'AI arms race' will impact the sustainable finance field (Bloomberg, 2023; Morgan Stanley, 2023; Stripe, 2023; The New York Times, 2023).

Figure 1-2 Industrial Revolutions



Note. Adapted from *How ICTs are accelerating the SDGs* (p.36), by the ITU, 2017, ITU News Magazine, 17. Retrieved from <https://www.ucc.co.ug/wp-content/uploads/2017/10/ITU-Magazine-How-ICTs-are-accelerating-the-SDGs.pdf>

When the SDGs were adopted in 2015, it was stated that data and technology could unlock the potential to not only monitor progress toward sustainable development as once traditionally used, but more importantly, to actively contribute through evidence-based policies and programs (UN Global Pulse & GMSA, 2017). This was followed in 2016 by the likes of the Group of Twenty (G20), which included sustainable digital finance as one of its 2030 workstreams, and the United Nations Environment Programme, which published recommendations in its *Fintech and Sustainable Development: Assessing the Implications* report (Blakstad & Allen, 2018a; Macchiavello & Siri, 2020).

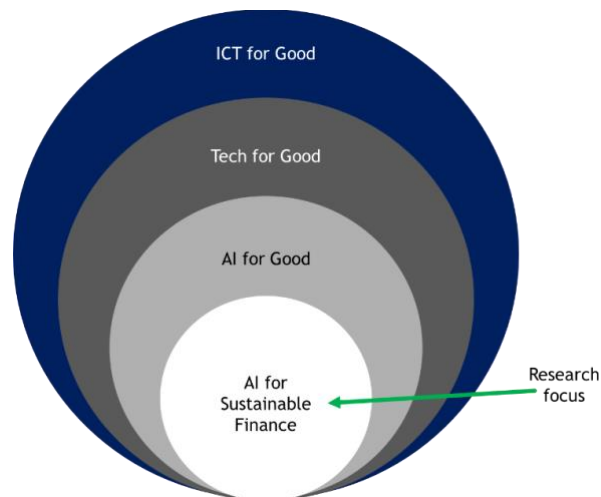
Meeting the SDGs will require action on several technological fronts, including better understanding the potential of digital innovations (Carè et al., 2023). For AI for sustainable

finance to support sustainable development, it must focus not only on the perceived benefits as imagined by those who develop them, but also on how the technologies (and associated benefits) are accessible, useful, and can be integrated into local contexts that vary economically, politically, and culturally (especially by the poorest or most vulnerable) (Arthur, 2009). On the one hand, AI for sustainable finance has been utilized to improve the quality of life for developing nations and enable greater access to basic human amenities for their populations. On the other hand, AI for sustainable finance is often not regulated by conventional financial regulators and might have negative effects on financial markets or exclude those without access (Pashang & Weber, 2021).

While AI for sustainable finance is relatively new in the literature and in practice, technology utilization to improve social and environmental outcomes is not. Information, and communications technology (ICT) was first introduced in the literature (Cornish, 1982; Melody & Mansell, 1986; Nooteboom, 1992) in the 1980s to represent technologies such as telephone networks, computer networks, television, and radio. In the sustainable development field, the most widely used reference to technology is ICT for development, a term that was also used in 2000 for the UN Millennium Development Goals (ITU, 2019b; UN, 2003). With advancements and variance in digital innovations, the term ICT no longer accurately describes the field as it once did and thus must be revisited. Therefore, ICT for good serves as an umbrella term for newer sub-fields such as AI for good (Clopath et al., 2019; Rolnick et al., 2019; Taddeo & Floridi, 2018); fintech for good (Alexander et al., 2017; Arner et al., 2020; Pashang & Weber, 2021); and AI for sustainable finance (Pashang & Weber, 2023) in both academic and industry literature. Figure 1-3 illustrates the focus of this research and highlights the evolution of

technology in sustainable development (i.e., from ICT for Good to AI for sustainable finance) within this scope.

Figure 1-3 Evolution of AI for Sustainable Finance and Research Focus



Note. This figure shows the various stages of technology in sustainable development as well as the focus of this research. Source: Author.

1.2 Theoretical Framework: AI and ESG practices as social innovations for sustainable finance

Despite the significance of the relationship between AI and sustainable finance, there is a dearth of theoretical underpinnings specifically for this growing field. To address this gap, this dissertation employs social innovation theory as an epistemological framework to understand AI's role as a social innovation in sustainable finance while incorporating ESG as an adjacent social innovation. ESG is examined as an independent, yet complementary, mechanism focused on institutional practices, with an emphasis on its limitations, particularly during the COVID-19 pandemic. This dual perspective offers a critical lens for analysing the research questions. To

establish this framework, 22 theoretical frameworks commonly attributed to AI were identified and analyzed through a scoping review. This process evaluated the strengths and shortcomings of these existing frameworks while considering the research focus.

Throughout this research, Westley's (2014 para. 1) interpretation of social innovation is adopted to address AI for sustainable finance: "A social innovation is any initiative (product, process, program, project, or platform) that challenges and, over time, contributes to changing the defining routines, resource and authority flows or beliefs of the broader social system in which it is introduced. Successful social innovations have durability, scale, and transformative impact." This viewpoint, rooted in complexity theory, resilience theory, and structuration theory (Westley et al., 2016), provides a foundation for examining AI as a social innovation. Similarly, Cajas-Santana (2014) posits that social innovations are embodied in shifts in behaviours and attitudes that result in new social practices, movements, and institutions, rather than simply the debut of new material products. This dissertation applies these theoretical perspectives to examine AI for sustainable finance as a social innovation.

Recognizing that AI alone cannot fully address the structural dimensions of sustainable finance, this research also positions ESG practices as an adjacent social innovation. While ESG aligns conceptually with social innovation theory, its ability to achieve systemic change remains questionable, particularly during crisis (Folger-Laronde et al., 2020). Investors rely on ESG insights to measure a firm against sustainability criteria to help support their investment strategies and decisions (Pashang et al., submitted). However, this research critiques ESG's limitations in achieving meaningful outcomes during crises, as further discussed in chapters 3

and 4. By examining the distinct yet interrelated roles of AI and ESG, this research contributes to the broader discourse on sustainable finance and social innovation theory.

Social Innovation Theory

The study of innovation began in the works of economists such as Smith (1776) and Jevons (1866) who were interested in its consequences and paradoxes, Schumpeter (1912, 1942) who viewed it as a dynamic and driving force that transforms economic, social, and institutional structures, and later Arthur (2009) who further advanced theory, definition, and language for the 21st century. Scholars (e.g., Fagerberg et al., 2012; van der Have & Rubalcaba, 2016) have studied new types of knowledge that have emerged in various fields that have contributed to social innovation studies. In a seminal systematic review of social innovation publications between 1986-2013, Van der Have & Rubalcaba (2016) identified the formation of four scholarly communities in the field's brief history. These included 1) community psychology; 2) creativity research; 3) social and societal challenges; and 4) local development. Social innovation has also been discussed by management scholars (e.g., Crossan & Apaydin, 2010; Damanpour, 1996) under sub-categories such as social entrepreneurship and social movements, while socio-technological dimensions have only appeared in innovation discourse and research more recently, including distinctions between technical and social innovation by sociologist William Ogburn (Cajaiba-Santana, 2014).

While still regarded as a new field of study in the social sciences, social innovation as a phenomenon has been present in the evolution of human societies for millennia (McGowan & Westley, 2015). The ability to invent and innovate is an innate part of civilization and has been present in our history as a way to respond to challenges and improve our quality of life

(McGowan & Westley, 2015). Historically, however, innovation has been promoted through public and private mechanisms, operated only by a few developed countries and international bodies (Nelson, 1993). These efforts have succeeded, to some degree, in fulfilling global sustainability needs but have fallen short of advancing sustainable development (Harvard Kennedy School, n.d.; InterAcademy Council, 2004; Juma & Yee-Cheong, 2005). It is undeniable that any globally pervasive innovation like AI demands attention for its effects on people and planet (B. Friedman & Hendry, 2019; Wynsberghe, 2021). Hence, with the experimental nature of social innovations like AI for sustainable finance, ethical safeguards, governance schemes, and policies must be in place to facilitate sustainable development (Wynsberghe, 2021).

Over the past two decades, scholars (e.g., Cajaiba-Santana, 2014; Mulgan et al., 2007; Westley et al., 2006; Westley & Antadze, 2010) have generated an abundance of definitions and concepts of social innovation with interpretations. Mulgan et al. (2007) defined social innovation as “innovative activities and services that are motivated by the goal of meeting a social need and that are predominantly developed and diffused through organizations whose primary purposes are social,” while Moulaert et al. (2017) have defined social innovation as a normative concept and practice, in that it is meant to improve society. A slightly different approach is taken by Castro-Arce et al. (2019), who view social innovation as processes that identify, evaluate, address, and achieve social needs and objectives that empower groups of people. Despite efforts to disambiguate competing, missing, and fragmented notions, there continues to be a lack of agreed clarity on what constitutes the field. This ongoing ambiguity presents a critical research gap: while numerous definitions exist, there is limited consensus on how social innovation is

operationalized across disciplines, particularly in times of crises. In the context of sustainable finance, this gap is even more pronounced as emerging technologies such as AI are positioned as tools to stabilize markets. However, the extent to which these technologies can contribute to systemic change remains unclear, calling for a more structured framework that connects social innovation theory with (financial) sustainability.

Guided by Westley's (2014 para. 1) definition, this research emphasizes critical aspects of social innovation relevant to sustainable finance. While prior research (e.g., Geobey et al., 2012; Katsamakas et al., 2022; Moore et al., 2012) has explored the role of sustainable finance as a strategy to fund, develop, or scale social innovations, the extent to which AI and ESG function as social innovations remains debated. While both are increasingly positioned as mechanisms for systematic change, the extent to which they demonstrate durability, scalability, and transformative impact remains unclear. These are key aspects of social innovations theory, as outlined by Westley (2014). Chapter 2 examines AI as a social innovation in sustainable finance at institutional and societal levels, highlighting its risks and benefits to planet, people, and profit in the wake of the pandemic. Chapter 3 evaluates the characteristics of AI-generated public sentiment data as a social innovation, contrasting it with conventional ESG performance data. ESG practices are critiqued for their inability to achieve the transformative outcomes posited by social innovation theory. Chapter 4 extends on these insights by comparing the impact of ESG and economic stimulus measures during the COVID-induced market volatility, offering nuanced perspectives on their respective roles in mitigating market volatility and promoting firm resilience. These theoretical insights provide the foundation for the research questions explored

in the following section, which interrogate the roles of AI and ESG as social innovations within sustainable finance during times of crisis.

1.3 Research Questions

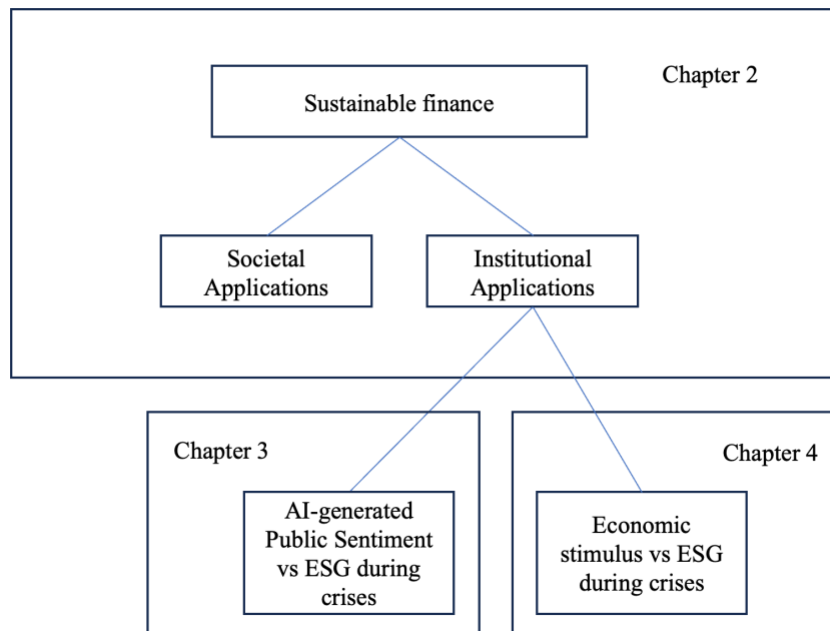
The interaction between AI, finance, and sustainability presents a compelling opportunity to address a discernible gap in the literature. AI and ESG have been increasingly discussed in relation to social innovation, yet the extent to which they meet criteria of durability and scale remains uncertain. While both have influenced sustainable finance, whether they function as true social innovations, as outlined by Westley (2014), remains insufficiently examined. This research therefore addresses this gap by investigating whether AI and ESG operate as social innovations in sustainable finance and assessing their impact on firm resilience, adaptability, and performance during economic uncertainty. By doing so, it contributes to the broader discourse on the evolving role of social innovation in promoting sustainable finance. This prompts the overarching research question: To what extent do AI and ESG function as social innovations in sustainable finance, particularly in crisis settings, and what are their implications for firm resilience and market stability or volatility? We present the sub-research questions below.

1.4 Organization of the Thesis and Sub-Research Questions

Recent discourse around AI has highlighted the concept of techno-solutionism (Pashang & Weber, 2023), which on one hand appears to promote and, on the other, inhibit sustainable development. This discourse is important as it reveals the double-edged nature of social innovation, whereby one can no longer discuss the benefits of AI without addressing its drawbacks. Conceptually this tension mirrors earlier tools and technologies developed to solve

challenges throughout the continuum of human activity (Friedman & Hendry, 2019). As a social innovation, AI follows this historical pattern, calling for careful attention to both its opportunities and inherent risks. Figure 1-4 illustrates how the proceeding chapters are positioned within this broader landscape of inquiry into sustainable finance.

Figure 1-4 Pathways Towards the Research Focus



Note. This figure shows how the three chapters are situated in relation to one another. The pathways reflect the interconnected roles of AI and ESG as dual social innovations within the guiding framework of social innovation theory. Source: Author.

Chapter 2 begins with an exploration of AI for sustainable finance to gain a comprehensive understanding of the enablers and inhibitors related to institutional and societal-level applications. While major proposals and reports were released by standard-setting and regulatory bodies leading up to 2020, the COVID-19 pandemic caused major setbacks to adoption and implementation, which, in turn, resulted in inconclusive data and lessons learned.

As the global community navigated out of the pandemic, stakeholders, through multilateral and cross-sector agreements, looked to renew governance mechanisms that mitigate new and pre-existing risks, while cultivating sustainability and facilitating innovation (Pashang & Weber, 2021). To critically assess this evolving landscape, the chapter employs a qualitative document analysis of academic studies, regulatory and policy publications, and industry reports. This methodological approach allows for a systematic review of governance frameworks and regulatory mechanisms, assessing both their potential to support sustainable development and their socio-ecological implications. Guided by this process, we asked: To what extent do AI and ESG function as social innovations, and how do they influence sustainable finance practices at institutional and societal levels during times of crises? We positioned this research to mediate the pathway towards the following chapters, which solely focus on institutional sustainable finance. Accordingly, we narrowed the scope to examine the efficacy and implications of AI as a social innovation in sustainable finance, focusing specifically on AI-generated public sentiment data in Chapter 3 and ESG performance as a form of social innovation in Chapter 4.

Chapter 3 builds upon the groundwork established in the preceding chapter, scrutinizing the effectiveness of AI-generated public sentiment data as a social innovation, particularly in the context of crisis events. Good management theory (Waddock & Graves, 1997) is used in this chapter to explore the relationship between ESG performance and financial performance, to gain insights into dynamic materiality, a concept that recognizes the fluid nature of investors' perceptions about which material ESG issues matter most in the context of global market environments (Eccles, 2020). With the focus of our study on the COVID-19 pandemic, this research explores the relationship between ESG performance and financial performance of

Canadian firms. Specifically, we asked: How does AI-generated public sentiment data compare with conventional ESG performance data in offering material insights about the financial performance of Canadian firms during the COVID-19 pandemic? While previous research has examined empirical evidence concerning firms in the United States, Europe, and G20 nations amidst the pandemic, at the time of writing, no prior study has presented unique insights or implications regarding how Canadian firms navigated this crisis. Key findings reveal that AI-generated public sentiment data correlates more strongly with financial returns and stock price volatility during this crisis than conventional ESG data, reflecting its potential as a social innovation. Furthermore, this study contributes both methodologically and theoretically to the literature. First, we use novel methods to examine how AI-generated public sentiment ratings compare to conventional ESG ratings in offering insights. Second, we contribute to theory by situating Waddock and Graves' (1997) notions (i.e., 'doing good by doing well') about good management in the context of crises. To our knowledge, this is the first study that investigates this line of reasoning in the context of the pandemic. To enhance our effort in connecting the theories to our empirical results and broadly to firms navigating through the pandemic, we incorporate Carroll's (2016, p. 3) views about economic responsibility being a "fundamental condition or requirement of existence" that is "required by society." Without an economic foundation, firms may not be able to sustain environmental and social practices, nor will ESG performance be rewarded in the absence of financial performance.

Chapter 4 builds on key findings from the preceding chapter by examining the comparative impact of economic stimulus and ESG performance on the resilience of Canadian firms during the market volatility induced by COVID-19. This chapter applies a crisis lens to

Waddock and Graves' (1997) conceptualizations of slack resource theory and good management theory, which propose that firms with slack resources and effective management possess greater flexibility to invest in ESG activities, thereby enhancing financial performance and corporate social responsibility. Further, we extend Waddock and Graves' (1997) conceptualizations of slack resource theory by proposing that economic stimulus, facilitated by fiscal space, may act as a mediating factor that generates slack resources for firms facing crisis-induced market volatility, thus enabling them to effectively address stakeholder expectations. We draw on these theories to help answer our research question: How does economic stimulus compare with ESG performance in 'immunizing' firms from COVID-induced market volatility? Our findings indicate that economic stimulus played a more significant role in stabilizing financial performance and reducing volatility than ESG performance. Building on chapter 3, this chapter offers a unique perspective on the impact of economic stimulus on variables such as market volatility and financial returns. Our findings from chapters 3 and 4 particularly highlight the nuanced ways that different factors influenced weekly abnormal returns and weekly price range, with observable variation across the pre-pandemic, pandemic, and post-pandemic periods.

The chapters are interconnected through the guiding framework of social innovation theory, using AI and ESG as dual social innovations that play a role in sustainable finance in distinct ways during times of crisis. By situating our analysis in Westley's (2014) interpretation of systemic transformation, this thesis explores how AI and ESG contribute to firm resiliency and adaptability within sustainable finance. This sequential approach advances the discourse on navigating uncertainty, emphasizing multidimensional frameworks grounded in social innovation theory.

This research makes key contributions to both empirical research and theory by critically examining AI and ESG as potential social innovations in sustainable finance, particularly in crisis settings. From an empirical perspective, it fills a gap in empirical studies by being among the first to systematically compare AI-generated public sentiment data with traditional ESG performance metrics in the Canadian context. It also advances understanding of the role of economic stimulus in shaping firm-level ESG engagement, an area that has remained underexplored in sustainable finance discourse. From a theoretical standpoint, this study extends slack resource theory by proposing that economic stimulus can serve as a crisis-induced form of slack, financial buffer that allows firms to navigate through volatility. Additionally, it applies good management theory to crisis conditions by integrating the concept of dynamic materiality and re-examining how firms manage stakeholder satisfaction and investor confidence. By framing AI and ESG within social innovation theory, this research evaluates their potential for systemic change in sustainable finance, applying Westley's (2014) criteria of durability and scale. Collectively, these contributions deepen the intersection of AI, ESG, and decision-making, expanding the theoretical and empirical discourse in this field.

Having established why social innovation theory provides a meaningful lens for studying AI and ESG in sustainable finance, it is important to ground this argument in the broader institutional and regulatory context in which these innovations operate. The questions raised in this opening chapter, about durability, scale, and systemic transformation, cannot be answered in abstraction. They require an understanding of how governance mechanisms, policies, and industry practices have shaped, and sometimes constrained, the evolution of AI for sustainable finance.

The next chapter therefore turns outward, situating AI and ESG within the wider landscape of sustainable finance governance. To do so, it employs a qualitative document analysis approach, systematically reviewing academic research, policy and regulatory documents, and industry reports. This allows for a careful mapping of how AI has been positioned, whether as an institutional tool to generate ESG insights for investors or as a societal tool for advancing financial inclusion, and whether current frameworks support or hinder its contribution to sustainable development. By laying this foundation, Chapter 2 clarifies the systemic backdrop against which the empirical analyses of later chapters unfold.

The chapters are interconnected through the guiding framework of social innovation theory, which allows AI and ESG to be examined as dual innovations with distinct orientations during times of crisis. This sequencing is intentional: Chapter 2 establishes the fragmented governance context in which these innovations operate, Chapter 3 evaluates AI sentiment as a dynamic signal of stakeholder satisfaction, and Chapter 4 compares this to the stabilizing role of ESG and fiscal stimulus at the firm level. Together, these studies provide complementary perspectives on how firms and financial systems navigated COVID-19 shocks.

By situating the empirical analyses within Westley's (2014) systemic lens, the thesis contributes both theoretically and methodologically. It extends slack resource theory through the notion of crisis-induced fiscal space, reframes good management theory for volatile contexts, and demonstrates how alternative data and conventional metrics capture different but overlapping dimensions of stakeholder satisfaction. More broadly, it argues that AI and ESG represent parallel pathways of social innovation, one emergent and experimental, the other

institutionalized and widely diffused, each carrying potential and limitations for advancing sustainable finance.

The following chapter begins this investigation by turning outward to the governance environment. Using a qualitative document analysis, it reviews how regulators, industry actors, and policymakers have positioned AI in relation to sustainable finance, and whether existing frameworks enable or constrain its contribution to sustainable development. This provides the backdrop against which the empirical analyses of Chapters 3 and 4 can be more fully understood.

2. AI FOR SUSTAINABLE FINANCE: INSTITUTIONAL AND SOCIETAL APPROACHES

In the second chapter of this dissertation, co-authored with Olaf Weber and published in May 2023, we conducted a comprehensive literature review on the evolution and expanding role of AI for sustainable finance. Two primary approaches were examined - institutional and societal. Institutional approaches are used to provide ESG insights to investors and stakeholders while societal approaches serve as digital services intended for underbanked and unbanked individuals through financial inclusion initiatives. Despite the growing reliance on such digital tools, particularly during the COVID-19 pandemic, governance mechanisms and regulatory frameworks, both in Canada and abroad, remain fragmented, underutilized, or inhibit progress toward the 17 SDGs. While major proposals and reports were released by standard-setting and regulatory bodies leading up to 2020, the COVID-19 pandemic indeed caused major setbacks to adoption and implementation, which in turn have also resulted in inconclusive data and lessons learned. As the global community has navigated out of the pandemic, policy makers, through multilateral and cross-sector agreements, are looking to renew governance mechanisms that mitigate new and pre-existing risks, while cultivating sustainability and facilitating innovation. This chapter provides key recommendations for stakeholders based on rigorous document analysis methodology. We employed content and thematic analysis to examine, interpret, and elicit meaning about whether governance mechanisms and regulatory frameworks exist to support sustainable development, and explore potential intended or unintended socio-ecological implications of such efforts. This analytical procedure involves finding, selecting, appraising, and synthesizing data contained in published documents (e.g., academic papers, industry reports,

organization websites) (Bowen, 2009). Further, documents obtained from various sources were analyzed using this approach as a way to verify and corroborate findings, which provides greater confidence and rigour in addressing our research question (Bowen, 2009).

This chapter has been revised and expanded from its published version to incorporate additional analysis and updated discussion that reflect subsequent developments in the field. The original publication is: Pashang, S., & Weber, O. (2023). AI for Sustainable Finance: Governance Mechanisms for Institutional and Societal Approaches. In Mazzi, F. & Floridi, L. *The Ethics of Artificial Intelligence for the Sustainable Development Goals* (pp 203-229). Springer Nature.

MANUSCRIPT BEGINS

2.1 Introduction

Artificial intelligence (AI) in financial services has become integrated into our global social fabric, particularly with the advent of the COVID-19 pandemic in 2020. While such financial technology (fintech) applications have undoubtedly changed the way money is spent, borrowed, invested, and saved — at various junctures of the financial system, they are increasingly being used to address sustainable development, which will be referred to in this paper as “AI for sustainable finance.”

Fintech emerged after the 2008 global financial crash (GFC) and has rapidly evolved into a commercial and mainstream service offering since 2018. The Financial Stability Board (FSB) defines fintech as “technologically enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on

financial markets and institutions and the provision of financial services” (FSB, 2021 para. 1). Put simply, fintech includes digital innovations used for financial services.

While the evolution of fintech began with start-ups addressing intermediation gaps left by the formal banking sector (Aaron et al., 2017), today some start-ups, challenger digital banks, government agencies and incumbent banks use various subsets of AI (i.e., machine learning, natural language processing, deep learning) to also address socially responsible investing (SRI) and financial inclusion - in hopes of progressing the 17 SDGs approved by the United Nations.

Despite the growing governance action and literature regarding AI and how it relates to formal financial systems (globally and regionally), governance mechanisms for AI for sustainable finance need to be urgently identified as studies are rare and the lack of agreed measures could contribute to fragmentation in future policy outcomes. To bring together a coherent conceptualization of AI for sustainable finance, this chapter develops a definition: AI that embeds social and environmental inclusion, ethics and collaboration into its design, development and implementation to accelerate sustainable development.

Only in the past few years have cross-sector partnerships and multilateral discussions between central banks, standard-setting bodies and policy makers inspired governance frameworks and recommendations (e.g., the Bali Fintech Agenda and the Maya Declaration on Financial Inclusion) that advance people and planet, and not solely profit. On the one hand, AI for sustainable finance has been shown to unlock or enable efficiencies for various actors or industries, while on the other, it has been shown to inhibit progress toward sustainable development by presenting new or existing unintended consequences. Without governance and

regulatory frameworks in place, such innovations may threaten the viability of modern financial systems and the livelihoods of the actors that contribute to them (UNEP, 2016).

With this in mind, the ongoing debate surrounding sustainable development challenges (for example, energy consumption, e-waste, privacy and predatory issues, gender bias and racialization) related to regulations, ethics and particularly governance are mounting. In response, intergovernmental organizations, central banks and regulatory bodies have had to carefully, yet expeditiously, adapt to the evolving ecosystem - mitigating risk through robust regulatory measures while cultivating sustainability and facilitating innovation. To unpack these implications, this chapter addresses AI for sustainable finance using the following structure.

The first section examines the SDGs and how AI for sustainable finance can achieve them. Technology utilization to improve social and environmental outcomes during the Fourth Industrial Revolution are well under way. In only a few years, AI for sustainable finance has evolved from historical data analysis to real-time information and recently to predictive modelling (ITU, 2018).

The second section considers two vantage points related to AI for sustainable finance. The first observes AI for sustainable finance at the institutional level, in the context of ESG investing. Specifically, in developed markets, firms use subsets of AI and big data (for example, stock prices, ESG risk data, public sentiment) to provide investors with sustainability insights. The second vantage point relates to AI for sustainable finance at the societal level, in the context of digital financial inclusion. Emerging and frontier market actors have integrated adjacent industries to bridge the gap between unbanked (and underbanked) populations and the financial

system, serving vulnerable individuals and small businesses that historically have not had equitable access to financial and/or technology resources and literacy (Cantú & Ulloa, 2020).

The third section discusses the COVID-19 pandemic and the unique challenges and opportunities it has presented in the context of AI for sustainable finance. For instance, in late March 2020, the Bank of Canada (BoC) suggested that “During this time of heightened public health measures intended to limit the transmission of COVID-19, some consumers and businesses are choosing not to use cash to limit potential exposure” (Carmichael, 2020 para. 6). Current trends indicate an increased acceptance of digital tools and digital identity, and consideration of digital currencies (Carmichael, 2020; Cheung, n.d.). As nations and institutions look to AI for sustainable finance to address pandemic-related circumstances, the SDGs could serve as a guidepost to accelerate innovation while confronting practices that may be exclusionary or pose unintentional consequences.

2.2 Data and Methodology

This chapter employs a qualitative document analysis approach (Bowen, 2009) to examine governance mechanisms and regulatory frameworks shaping AI in sustainable finance. The goal was to determine whether such mechanisms support sustainable development and to identify potential socio-ecological implications of these practices. Document analysis is particularly suitable here because it allows for systematic review and interpretation of existing texts to generate insights where primary data collection is not appropriate.

Data Sources and Search Strategy

The analysis drew on a broad set of secondary sources produced between 2008 and 2023, a period covering the emergence of fintech after the global financial crisis through the disruptions of the COVID-19 pandemic. Search terms included combinations of “AI for sustainable finance,” “fintech governance,” “ESG investing,” “digital financial inclusion,” “regulatory sandboxes,” and “AI ethics and governance.”. Sources were gathered from:

- **Academic literature:** peer-reviewed journal articles, books, and book chapters accessed through Scopus, Web of Science, and Google Scholar.
- **Policy and regulatory documents:** publications from the FSB, BIS, IMF, World Bank, OECD, G20 communiqués, and UN agencies.
- **Industry and practitioner reports:** white papers, consultancy reports, and documents from industry associations (e.g., KPMG, Mastercard, Global Legal Group).
- **Organizational and institutional websites:** fintech firms, AI-driven ESG providers, NGOs, and multilateral initiatives (e.g., Alliance for Financial Inclusion).

Inclusion and Exclusion Criteria

Documents were included if they:

1. Explicitly addressed AI or fintech in the context of sustainable finance, ESG investing, or financial inclusion;
2. Originated from a recognized academic, regulatory, or industry source; and
3. Contained substantive discussion of governance, policy, or sustainability implications.

Excluded were duplicates, promotional or marketing materials without analytical content, and documents unrelated to financial applications of AI. Only English-language documents were reviewed, which tends to introduce a bias toward Global North perspectives.

Analytical Procedures

The analysis proceeded in two stages:

1. **Content analysis** identified explicit references to governance frameworks, regulatory mechanisms, and sustainability outcomes. Text was coded for recurring concepts such as regulation, risk mitigation, financial inclusion, and ESG disclosure.
2. **Thematic analysis** was used to interpret the coded material inductively. Themes emerged around governance mechanisms, institutional versus societal applications, intended benefits (e.g., efficiency, inclusion), and unintended consequences (e.g., energy intensity, bias, exclusion).

Coding was conducted manually by the lead author, drawing on an initial framework informed by the research questions, then refined through iterative readings. Findings were triangulated by comparing claims across academic, policy, and industry sources. For example, when an industry report highlighted the benefits of AI-driven financial inclusion, these claims were cross-checked against peer-reviewed literature and NGO reports to assess credibility.

Rigor and Validity

Triangulation across diverse document types enhanced the robustness of the analysis. Iterative review cycles refined emerging themes and reduced the risk of premature closure.

Transparency was ensured by documenting search strategies, coding decisions, and inclusion/exclusion rationales. This multi-source approach increased confidence in the findings and addressed subjectivity inherent in qualitative research.

Limitations

This method has limitations. It relies on publicly available documents, which may not fully capture proprietary or confidential practices. The restriction to English-language sources biases the analysis toward Global North contexts, limiting representation of Global South perspectives where financial inclusion initiatives are most pronounced. Finally, document analysis cannot establish causal claims; instead, it offers interpretive insights into how governance frameworks are articulated and debated in literature and practice.

2.3 AI and the SDGs

This paper adopts the following definition of sustainable development by Griggs et al. (2013): “Development that meets the needs of the present while safeguarding earth’s life-support system, on which the welfare of current and future generations depends.” In 2015, the United Nations introduced 17 SDGs as a framework to address global challenges such as poverty, climate change and numerous inequities by 2030 (UN, 2019a). When the SDGs were agreed to, it was stated that data and technology could unlock the potential to not only monitor progress toward sustainable development as once traditionally used but, more importantly, to actively contribute through evidence-based policies and programs (UN Global Pulse, 2017). This was followed in 2016 by the likes of the Group of Twenty (G20), which included sustainable digital finance as one of its 2030 workstreams, and the United Nations Environment Programme, which

published recommendations in its Fintech and Sustainable Development: Assessing the Implications report (Blakstad & Allen, 2018b; Macchiavello & Siri, 2020).

Meeting the SDGs will require action on several technological fronts, including better understanding the potential of digital innovations. For AI for sustainable finance to support sustainable development, it must focus not only on the perceived benefits as imagined by those who develop them but also how the technologies (and associated benefits) are accessible, useful and can be integrated into local contexts that vary economically, politically, and culturally (especially by the poorest or most vulnerable) (Arthur, 2009). On the one hand, AI for sustainable finance has been utilized to improve the quality of life for developing nations and enable greater access to basic human amenities for their populations. On the other hand, AI for sustainable finance is often not regulated by conventional financial regulators and might have negative effects on financial markets or exclude those without access.

Historically, innovation has been promoted through public and private mechanisms, operated only by a few developed countries and international bodies (Nelson, 1993). These efforts have succeeded, to some degree, in fulfilling global sustainability needs but have fallen short of advancing sustainable development (Harvard Kennedy School, n.d.; InterAcademy Council, 2004; Juma & Yee-Cheong, 2005). Addressing these gaps requires effective cross-sector partnerships between municipal, federal and international actors and input from end users (recipients and local stakeholders) contributing to the process. Within the global innovation system, the difficulties of utilizing technological innovation for sustainable development have been addressed in a variety of ways, such as through financing, formation of research networks, setting priorities, international aid and trade agreements, and action research feedback loops

connecting end users and innovators (Harvard Kennedy School, n.d.). To some degree, these interventions have altered institutional norms and configurations over the past few years, yet they are poorly described in the literature. Little is known beyond their respective fields, making it difficult to contribute to enhancing AI for sustainable finance in practice and scholarly discourse.

2.4 The Promise of AI for Sustainable Finance

A Brief History

The GFC of 2008 and its aftermath caused enormous turmoil and led to an extended period of low growth and instability across the international political economy (UNEP, 2016). This crisis originated from exorbitant risk-taking by US banks on subprime mortgages, which burst the housing bubble, triggered the collapse of the banking sector and led to an unprecedented “credit crunch” around the world (Flammer & Ioannou, 2021). As a result, numerous governance and regulatory measures infused by the G20 were implemented to reshape the global financial system. After the devastating impacts the GFC had on people and planet, investors and stakeholders turned to sustainable finance (e.g., ESG investing) in efforts to interrogate non-financial criteria related to climate change, environmental disasters, poor corporate governance and investment risks each of these posed (Townsend, 2020). At the same time, financial inclusion initiatives were established by G20 leaders (for example, the Financial Inclusion Experts Group, Global Partnership for Financial Inclusion [GPFI]); central banks of emerging markets (for example, the Alliance for Financial Inclusion and its release of the Maya Declaration on Financial Inclusion); and the United Nations (e.g., the Task Force on Digital Financing of the Sustainable Development Goals), to name a few (Arner et al., 2020).

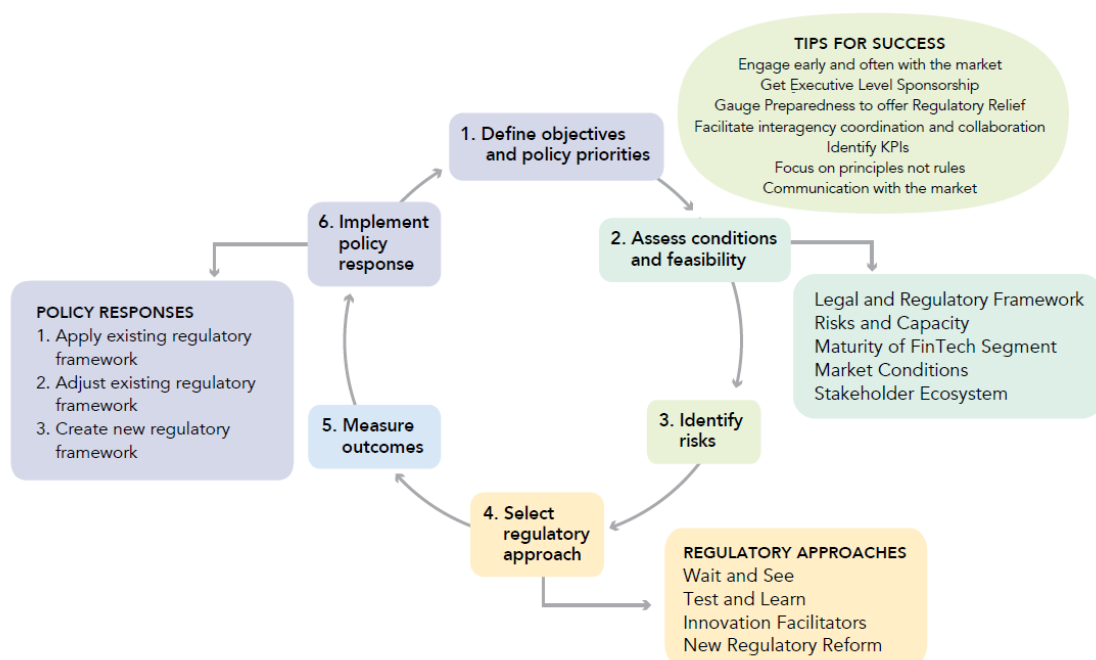
While AI for sustainable finance is relatively new in the literature and in practice, technology utilization to improve social and environmental outcomes is not. Upon reviewing the literature, information and communications technology (ICT) was first introduced in the literature (Cornish, 1982; Melody & Mansell, 1986; Nooteboom, 1992) in the 1980s to represent technologies such as telephone networks, computer networks, television and radio. In the sustainable development field, the most widely used reference to technology is “ICT for development,” a term that was also used in 2000 for the UN Millennium Development Goals (ITU, 2019b). With advancements and variance in digital innovations, the term ICT no longer accurately describes the field as it once did and thus must be revisited. The authors posit that ICT for good serves as an umbrella term for newer fields such as AI for good (Clopath et al., 2019; Rolnick et al., 2019; Taddeo & Floridi, 2018); fintech for good (Alexander et al., 2017; Arner et al., 2020); blockchain for good (Aganaba-Jeanty et al., 2017; Kewell et al., 2017; Sylvester, 2019); and big data for good (IGEL, 2014; Maarroof, 2015; Marsden & Wilkinson, 2018), in both academic and industry journals. To this end, stakeholders must be cautiously optimistic about advancing AI’s remarkable depth, power and speed in their efforts to accelerate sustainable development.

Recent Governance Responses

Cross-sector partnerships and multilateral efforts by bodies such as the FSB, Bank for International Settlements, the G20, Organisation for Economic Co-operation and Development (OECD) and numerous UN agencies have made some progress. Figure 2-1 depicts a process recently introduced by the World Bank Group, offering guidance on regulatory approaches toward fintech (World Bank, 2020). Despite such efforts, global adoption and implementation to

integrate such frameworks are largely missing (Fay, 2019). This trend is also evident across developed markets such as Canada and other G20 members (for example, China, the European Union, India and the United States), where regulatory bodies are still working to investigate and implement modifications.

Figure 2-1 Process to Identify Regulatory Approaches and Policy Responses toward Fintech



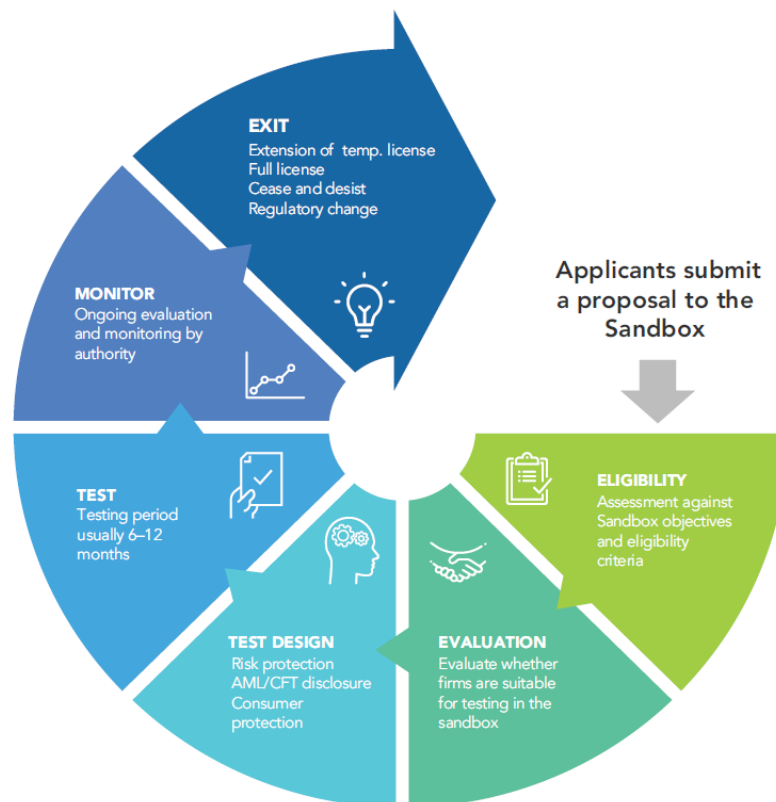
Source: (World Bank, 2020).

In 2018, the World Bank and the International Monetary Fund (IMF) launched the Bali Fintech Agenda paper, which proposed a framework on high-level fintech issues that countries should consider in their domestic policy discussions (World Bank Group, 2018). The report presented 12 policy proposals that cover issues related to enabling fintech, ensuring financial sector resilience, addressing risks, financial inclusion and promoting international cooperation.

While global cross-sector agreements such as the Bali Fintech Agenda have offered blueprints for AI for sustainable finance, it is not clear where member nations stand relative to these proposals presently. The pervasiveness of the COVID-19 pandemic has since caused reprioritization and major setbacks to such governance implementations, which in turn have resulted in inconclusive data and lessons learned. The last known review of country responses was carried out by the World Bank and IMF in 2019 (IMF & World Bank, 2019). Findings from the report included three major themes. First, common in nearly all regions are critical infrastructural and regulatory gaps (IMF, 2019). Second, monitoring of entities and activities is still confined within conventional regulatory parameters (IMF, 2019). Third, legal frameworks to address issues are widely missing (IMF, 2019). In its regional overview, the report highlighted the following: Africa has experienced rapid growth of mobile money in a push toward increased financial inclusion, but differences in regulatory approaches are noticeable and reactive to the pace of change (IMF, 2019). East Asia has made significant advances in all major aspects of fintech. To keep up with this pace, regulators have established fintech units and regulatory “sandboxes” to respond to various risks (e.g., consumer and investor protection concerns, financial stability and integrity) (IMF, 2019). Entities utilize fintech sandboxes to test solutions in controlled environments to expose potential risks and benefits. Figure 2-2 shows the various phases of a fintech sandbox lifecycle (World Bank, 2020). The European market is also rapidly growing but is distributed unevenly. While the European Union has enforced two major regulations (the General Data Privacy Regulation and Payments Services Directive 2) in 2018, their implications are yet to be seen. In West Asia, Central Asia and North Africa, adoption and progress are gradual, with concentration of activities only in a few countries and sectors.

Regulatory responses vary widely across the Americas, with Latin American and Caribbean nations still trailing behind Canada and the United States.

Figure 2-2 A Typical Sandbox Lifecycle



Source: (World Bank, 2020).

Note: AML/CFT = anti-money laundering/combating the financing of terrorism.

While some major AI for sustainable finance advancements have been made in Canada, very little has followed with regard to governance and policy, and agreed-upon frameworks around their functions are ad hoc, incomplete and insufficient. In Canada, there is no single federal or provincial regulatory body that has jurisdiction over such firms. Instead, regulations

are dependent on the types of services being offered by such firms (Global Legal Group, 2020). This notion of light-touch regulation has some concerned about bad behaviour by firms, renewing fears of a GFC-like scenario (Fay, 2019). Canadian regulators such as the Department of Finance, the Competition Bureau and some provincial agencies have made attempts at developing a fintech regulatory framework (Global Legal Group, 2020). The Ontario Securities Commission, the Autorité des marchés financiers in Quebec and the Canadian Securities Administrators are currently utilizing fintech sandboxes to experiment with various solutions (KPMG, 2019). Separately, the federal government in its 2018 Budget Implementation Act, Bill C-74, introduced changes (for example, the Bank Act, Trust and Loan Companies Act and Insurance Companies Act) in favour of fintech to provide financial institutions with new abilities (KPMG, 2018). What follows is an account of how these factors correspond to AI for sustainable finance in institutional and societal scenarios.

2.5 Institutional and Societal Approaches

Three major AI for sustainable finance approaches have emerged related to achieving the SDGs. The first is at the institutional level and involves redirecting the allocation of existing financial resources toward activities such as ESG investing. The second is at the societal level and includes the expansion of financial resources through financial inclusion to support the SDGs. The third is at the regulatory level and uses technology (regulatory technology or “regtech”) to (re)design enhanced financial governance systems (Arner et al., 2020). The following explores the first two approaches, which are central to the focus of this chapter.

ESG Investing

It is widely studied that SRI can support climate action (Eccles et al., 2014; Geobey et al., 2012; Weber & Feltmate, 2016). The thirteenth SDG aims to “take urgent action to combat climate change and its impacts” by integrating measures into national policies and institutional capacity building (UN, 2019a).

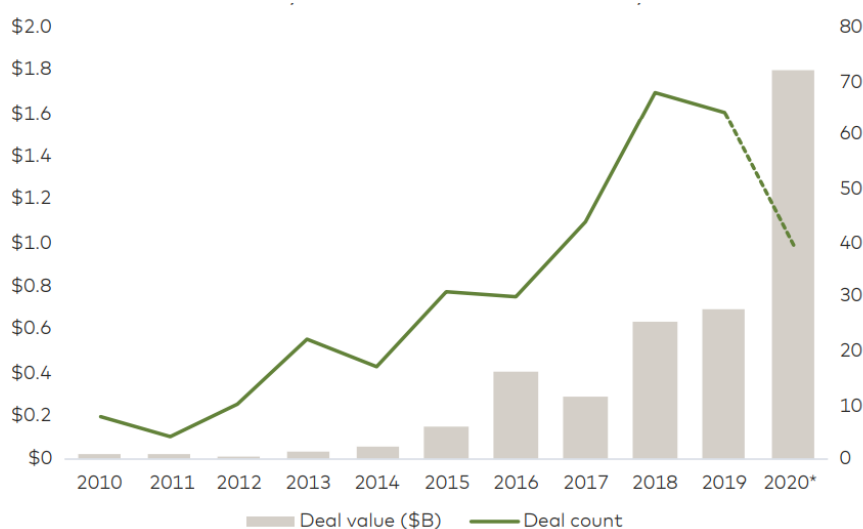
This section explores whether and how AI for sustainable finance could be used by ESG data firms that provide investors with non-financial performance information. Sustainable finance and AI are both major policy areas concerning stakeholders across sectors, exemplified by numerous initiatives by researchers and policy makers across G20 member states, the United Nations and the European Commission (Arner et al., 2020). Despite this, a paucity still exists in how they interact and whether additional governance and regulatory considerations are necessary. This was the case with the European Commission’s Sustainable Finance Action Plan, which made no mention of AI or fintech (Arner et al., 2020). Further, despite the growing availability of computational resources within financial institutions and the emergence of fintech more than a decade ago, existing solutions have only recently evolved to correspond with the growing interest in SRI and the abundance of big data related to ESG (Monteleoni et al., 2013; Weber & Feltmate, 2016).

Pre-existing complexities in the ESG domain have, for some time, prompted stakeholders to demand alternative ESG data. For instance, Eccles and Strohle (2018) stated that despite the growing appetite for data and empirical evidence showing a correlation between ESG performance and financial outcomes, the field remains unorganized and without universally agreed-upon standards (Eccles et al., 2014; Khan et al., 2016). With more than 100 data

providers (e.g., Vigeo Eiris, KLD, MSCI, ISS-oekom, Sustainalytics, Morningstar) in the ESG ecosystem, their incomplete efforts to standardize metrics, indicators and methods have created a variance in ratings and recommendations that confuse and misinform investors and undermine the soundness of ESG disclosure (Eccles & Strohle, 2018; GISR, 2018). Further, conventional ESG providers struggle in three major ways: first, ESG data is mainly sourced from company disclosure materials; second, ESG scores and data are typically at least a year old; and third, there are discrepancies and a lack of standardization among data providers (Folger-Laronde et al., 2020; Malinak et al., 2018).

Thus, some investors have turned to AI-driven ESG firms that consume big data and apply subsets of AI such as machine learning and natural language processing (NLP). Such tools are currently being used by asset managers, asset owners and quantitative managers who seek real-time alternative ESG data and analytics to support their clients' investing needs. Figure 2-3 shows venture capital funding in institutional fintech since 2010 (Mastercard, 2020).

Figure 2-3 Venture Capital Activity in Fintech and Sustainability



Source: (Mastercard, 2020)

(www.mastercard.com/news/media/bz5nmfg4/mastercard_start_path__pitchbook_fintech_for_good_report.pdf).

Note: *As of October 28, 2020.

In 2013, Truvalue Labs, one of the first AI-driven ESG data providers, was founded (Truvalue Labs, 2020a). Truvalue Labs analyzes public sentiment from alternative sources such as news media, think tanks, social media, non-governmental organizations (NGOs) and academic journals related to company ESG performance (Serafeim, 2020). Specifically, Truvalue Labs uses AI to analyze unstructured big data from more than 100,000 sources, such as analyst reports, news and social media, and government sources, and incorporates the Sustainability Accounting Standards Board's 30 materiality classifications to generate scores (0–100) (Serafeim, 2020). It is noted that transparency and validation are provided to the user by enabling them to track the source of information that informs the sentiment analysis. For instance, a drilling company could receive positive sentiment following news of their investment to improve waste and hazardous materials management, materials sourcing and product safety. Facebook, on the other hand, could receive negative sentiment due to exposure to data privacy issues, concerns about regulatory pressure and user rights (Serafeim, 2020). It has been reported that Truvalue Labs's sentiment analysis can also codify the degrees of positivity or negativity, instead of just the conventional binary approach: positive versus negative sentiment. According to (Serafeim, 2020), AI will make attempts to assign a more negative score to an event such as an oil spill that harms several people or communities and a less negative score to an event that causes minor injuries to one person.

Related Governance Challenges

With the rising demand for AI for Good offerings, governance mechanisms must confront the duality of what is considered ‘good’. While AI-driven ESG solutions can be useful to investors when evaluating a firm’s sustainability activities, it is not clear whether the algorithms that power such solutions have considered ethics, inclusion and environmental factors that could potentially compromise progress toward the SDGs. A study (Vinuesa et al., 2020b) published in *Nature* revealed that while AI enabled the accomplishment of 134 SDG targets, it inhibited the progress of 59. The study indicated that failure to enforce governance and regulatory oversight for AI for sustainable development could result in negative societal and environmental implications (Vinuesa et al., 2020b). For instance, AI-driven automation can lead to job displacement, which may disproportionately affect low-income workers and exacerbate economic disparity. Further, the growing energy demands of AI systems could contribute to higher carbon emissions and water usage (for cooling), which impact sustainability efforts. Privacy, data security, and bias challenges may also increase, which may have consequences for those who have typically been marginalized from financial and social services.

From an ethics and inclusion perspective, key aspects that require governance attention include transparency, equity, auditability and accountability. For instance, different algorithms that process the same raw data may ultimately produce different outcomes, which may have discriminatory, exclusionary and exploitative implications (Ehrentraud et al., 2020). A study surveyed numerous jurisdictions and found that none enforced any regulatory requirements for financial institutions that employ AI (Ehrentraud et al., 2020). Another growing subdomain of AI ethics is sustainable AI, which confronts whether AI itself is environmentally sustainable when

considering computing power and energy consumption required for training AI (Wynsberghe, 2021). For instance, Strubell et al. (2019) showed that training a single NLP model, which uses deep learning, could produce the same amount of carbon dioxide (CO₂) (around 600,000 pounds) as five cars over the cars' entire lifespan (Wynsberghe, 2021). Thus, policy makers must continue refining regulation and legislation standards that address these ethical considerations.

To address some of these challenges, nations such as Singapore have released frameworks to promote AI fairness, ethics, accountability and transparency, while the Netherlands promotes soundness, accountability, fairness, ethics, skills and transparency (Ehrentraud et al., 2020). The Canadian Institute for Advanced Research's Pan-Canadian AI Strategy (appointed by the federal government in 2017), has been working to develop the world's first national AI strategy, including a work stream titled "AI & Society" (CIFAR, n.d.). Other nations, particularly in the G20, also have efforts under way that look to expose and address negative implications for society (Ehrentraud et al., 2020).

Financial Inclusion

The 2030 Agenda for Sustainable Development recognizes that poverty is the greatest global challenge, and its eradication is a requirement for sustainable development. The first SDG aims to "end poverty in all its forms everywhere"¹ and pushes for robust protection systems and spending on primary services to help individuals escape poverty.

This section explores whether and how AI could help promote an inclusive digital economy that provides financial services to the unbanked (those who have no bank account or

¹ See <https://sdgs.un.org/goals/goal1>.

transactions through a mobile money provider) and underserved individuals living in poverty. Around 700 million people today live on less than \$2 per day and 1.3 billion people are multidimensionally poor (UNDP, 2019). Some priority areas and associated targets include reducing poverty by 50 percent (by 2030), improving access to sustainable livelihoods and entrepreneurial opportunities, empowering people living in poverty with support systems and addressing the disproportionate impact of poverty on women (UN, 2019d). While extreme poverty has declined, this trend has slowed and the United Nations warns that we are not on track to achieve its 2030 global target (less than three percent living in extreme poverty) (UN, 2019d). The COVID-19 pandemic has further exacerbated circumstances for the most vulnerable. Since 2020, the following trends have been observed: global poverty (SDG 1)² has increased for the first time in decades; inequalities and dangers that women and girls face have increased (SDG 5);³ the world is facing the worst economic recession since the great recession (SDG 8)⁴; and investment in fossil fuels remains higher than in climate action (SDG 13)⁵ (UN, n.d.-b).

Financial inclusion is one of the UN Global Compact categories in which the financial sector can play a role in addressing the SDGs, with about 1.7 billion people remaining unbanked (Weber, 2018; World Bank Group, 2017). The United Nations states that to eradicate poverty by 2030, “affordable technological solutions have to be developed and disseminated widely” (UNDP, 2019 para. 2). The role of technology, concerning financial inclusion, has been discussed by stakeholders after the onset of the GFC. In 2008, policy makers established the Alliance for Financial Inclusion while G20 leaders endorsed a Financial Inclusion Action Plan at

² Ibid.

³ See <https://sdgs.un.org/goals/goal5>.

⁴ See <https://sdgs.un.org/goals/goal8>.

⁵ See <https://sdgs.un.org/goals/goal13>.

the Seoul Summit in 2010 and created the GPFI (Gabor & Brooks, 2017). In 2015, the United Nations emphasized financial inclusion in multiple SDGs (numbers 1, 5 and 10) and noted the value of technology in accelerating them (UN, 2017). In 2018, a collaboration between the IMF and World Bank gave rise to the Bali Fintech Agenda, which established a broad road map to appropriately implementing digital financial inclusion (Sahay et al., 2020).

In the Global South (for example, China, Ghana, India, Kenya, Myanmar, Peru and Uganda), AI for sustainable finance has also been advanced by governments, mobile money networks and NGOs to help address the needs of individuals who are generally unbanked or experiencing poverty. Offerings include income and liquidity support, filing tax returns, flexible loan repayments, lower transaction costs and increased transaction limits, which are helping shift away from conventional financial service practices (Sahay et al., 2020). AI for sustainable finance firms such as CreditVidya⁶ and Zest Finance use alternative data such as “digital fingerprinting” captured from an individual’s device, browser and social media activity to predict creditworthiness (AI, 2020; CreditVidya, 2020; LenddoEFL, 2020). In Kenya, M-Shwari (M-Shwari, 2020) uses a mobile money system (M-Pesa) to incorporate phone history in its assessment of credit risk. With 20 percent of adults (37 million users) in Kenya actively using this service, M-Shwari is seen by some as a financial inclusion success story (Cantú & Ulloa, 2020; M-Shwari, 2020). The service incorporates predictive algorithms and AI to analyze social and telecom data to assess creditworthiness. Within a few minutes, a credit score is produced, offering the terms of the loan (M-Shwari, 2020). On a macro level, insights about the economic health and resilience of a community can also be extrapolated from the use of mobile financial

⁶ See <https://creditvidya.com/how-it-works>.

services, monthly airtime top-up patterns and the purchase of value-added services (UNDP, 2019). Despite their potential to contribute to the SDGs, these examples (such as institutional ones noted above) must be approached with great caution due to risks related to data security, accountability, and bias.

With regard to global remittances, recorded annual flows in 2018 to low- and middle-income nations reached US\$529 billion (a 9.6 percent increase since 2017) (World Bank Group, 2018). Conventional transactions pose barriers such as high fees, lack of traceability and beneficiaries who lack formal identification or bank accounts (World Bank Group, 2018). To address this, AI for sustainable finance related to remittance transactions may remove such constraints by ensuring transparency of inflows, directing remittances toward socially responsible purchases, offering cheaper transaction fees (a reduction from 10 to three percent), securing the privacy of individuals and creating digital IDs that can be used for other money transfers (UNDP, 2018). AI for sustainable finance is also being used to provide unbanked individuals with insurance rates for farming, credit scores and loans through consent-based alternative data sources such as digital (email, social media and mobile transactions), behavioural and psychometrics. Despite much progress, governance mechanisms are necessary to ensure such initiatives address inclusion, ethics and collaboration in their design, development, and implementation.

Related Governance Challenges

While anecdotal indications seem to show great potential for AI for sustainable finance when considering financial inclusion, risks and unintended consequences have been hard to quantify and are loosely studied. In order for AI to best serve financial inclusion, “exclusive

inclusion” must be addressed. Broadly defined, exclusive inclusion is the deliberate or unintentional practice of “including” or aiding particular groups of people while knowingly or unknowingly excluding others. The concept can also refer to providing services that (from the perspective of the provider) seem to address recipients’ needs while overlooking or ignoring their other interconnected needs. Often, such practices worsen pre-existing risks or trigger new ones.

For instance, AI for sustainable finance has the potential to close gender gaps and ensure women (currently one billion are unbanked) are not left behind, however, special attention needs to be paid to pre-existing barriers for women such as access to technology (smartphones and internet access), cultural and social norms, and digital and financial literacy (D’Silva et al., 2019; Sahay et al., 2020). Undocumented individuals (particularly women) could face even more risks and complexities. This is important given AI for sustainable finance is often the only viable option for many refugees who are seeking loans. Further, as the spread of credit has increased from Global North countries to such individuals, it has resulted in uneven distribution of credit access and livelihood support, since some (e.g., entrepreneurs) are deemed worthy of loans while others experience further exclusion (Bhagat & Roderick, 2020). Critics of such approaches suggest that such options are an extension of financialization and situate marginalized people as recipients of unregulated financial services through technology (Gabor & Brooks, 2017).

To cultivate dignity, agency and benefit to underbanked and unbanked individuals, efforts should be made by AI for sustainable finance firms to include recipients in the design, development, implementation, and feedback phases. The principle of Sankofa, derived from the Akan people of Ghana, illustrates this mindset (Temple, 2010). It states that to collectively shape

and inform the future, we must look back and recognize the past, or anything about us, done without us, does nothing for us (Temple, 2010). This concept underscores the importance of clear and effective regulatory oversight and governance frameworks and agreed-upon metrics for monitoring. While some work has been carried out by the likes of the OECD, the G20 and the ITU, these efforts must be broadened to reflect the diversity of global contexts to generate buy-in and participation by stakeholders (UN, 2019c).

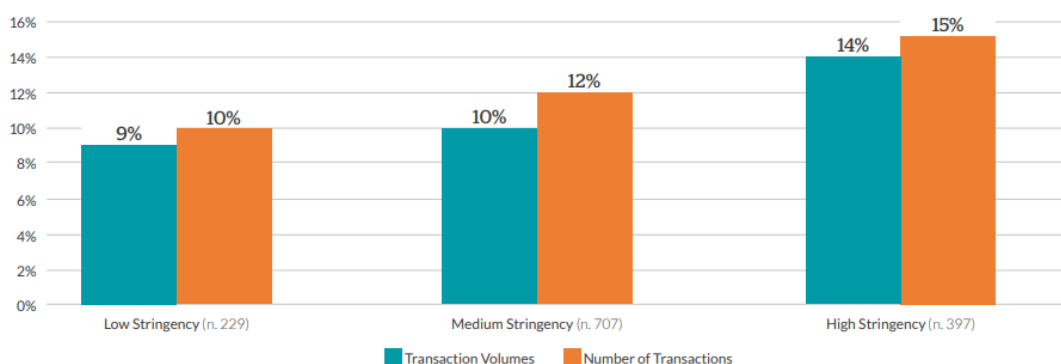
2.6 Navigating through a Pandemic

COVID-19: A “Natural Experiment”

The COVID-19 pandemic is the most devastating and pervasive challenge in modern history. This global emergency has been classified as a “mega-crisis” or a system that consists of numerous crises, each with interconnected parts, drivers and consequences (Pashang, 2020). Almost two years have gone by since cases of COVID-19 first appeared in Wuhan, China. Despite recent vaccination programs, more than 220 million cases and more than 5 million deaths have been confirmed worldwide, and the pandemic continues to spread havoc (WHO, n.d.). Due to physical distancing and lockdown measures resulting from the pandemic, financial services designed around cash and in-person interactions to open accounts, determine creditworthiness or provide financial literacy, significantly shifted to contactless and cashless transactions, deployment of government support measures and lending (Sahay et al., 2020). Fintech has evolved from spending to lending to fill existing gaps within traditional financial services (Sahay et al., 2020).

The global demand for fintech services increased dramatically during the pandemic, particularly in response to the varying severity of lockdown restrictions enforced across regions. A major cross-sector study analyzed 1,385 fintech firms across 169 countries and found that services in markets with more stringent lockdown restrictions reported larger growth in volume and number of transactions (CCAF et al., 2020). Figure 2-4 illustrates that fintech firms situated in regions with the highest stringency measures reported 50 percent more volume and transactions (year-on-year Q1 to Q2) than those in the lowest quantile (CCAF et al., 2020).

Figure 2-4 Transaction Volumes and Number of Transactions under Low, Medium and High COVID-19

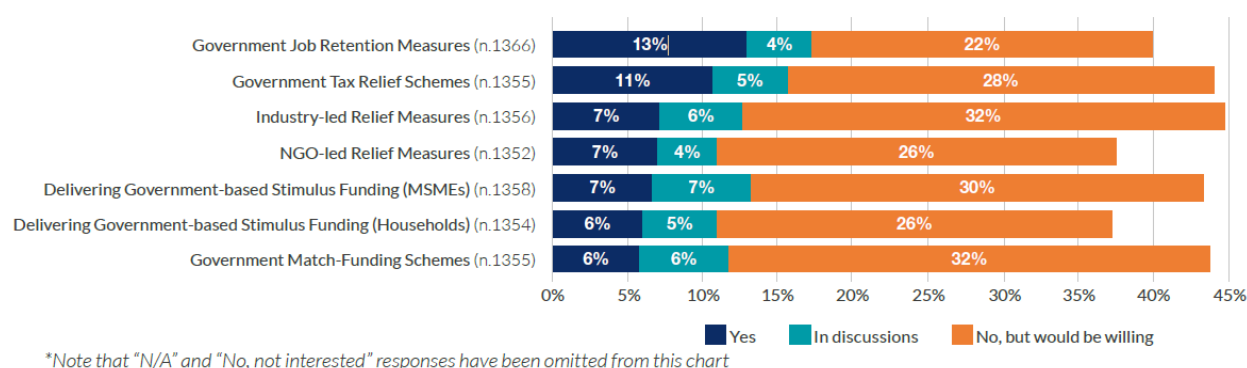


Source: (CCAF et al., 2020).

In many parts of the world, fintech has supported individuals and businesses through challenges caused by the pandemic. For instance, small and medium-sized enterprises (SMEs) in Latin America that were in need of relief were able to access government transfers through digital disbursements (Cantú & Ulloa, 2020). Through the mobile app of a state-owned bank, the federal government in Brazil was able to increase access for unbanked and underbanked

individuals to receive aid. Similar occurrences took place in Peru and Argentina via municipalities, while in Mexico, fintech firms applied alternative credit rating technology to provide loans (approved in 24 hours) at a lower cost to SMEs. Figure 2-5 highlights areas where AI for sustainable finance played a role in supporting governments around the world with pandemic relief measures (CCAF et al., 2020).

Figure 2-5 Implementation or Delivery Partner in COVID-19-Related Relief Measures of Schemes, All Fintech Verticals (% of Respondents)



Source: (CCAF et al., 2020).

Note: "N/A" and "No, not interested" responses have been omitted.

In Canada, the pandemic accelerated the digitalization of the economy and reignited debate about the future of cash and banking. Before the pandemic, the BoC had piloted Project Jasper, one of the most comprehensive crypto-based central bank digital currencies in the world (FSB, 2017; IMF & World Bank, 2019). Less than a year after the onset of the pandemic, with growing hesitancy among consumers about using cash, BoC Deputy Governor Timothy Lane stated that "if we want to be ready to develop any kind of digital central bank product, we need to move faster than we thought was going to be necessary" (Gordon, 2020). For central banks in

emerging and frontier markets, financial inclusion has been among the main reasons for exploring cryptocurrencies such as stablecoin (Bank for International Settlements, 2020).

Related Governance Challenges

The FSB has indicated that fintech does not yet (by itself) pose significant risks (Restoy, 2019; Sahay et al., 2020). From a macroeconomic perspective, given appropriate regulations are in place, AI for sustainable finance may offer positive outcomes by enabling greater portions of the population to participate in formal economic activity. This was supported by the IMF, which suggested AI for sustainable finance has the potential to enhance the efficacy of post-pandemic macroeconomic policies, when considering income creation and employment (Sahay et al., 2020).

Notwithstanding these opportunities, it is not yet understood whether or how such opportunities could instead exacerbate pre-existing and/or new risks to those they intend to serve. Looking to prior examples, the rapid development of various fintech has resulted in structural unintended consequences, leading to a spike in predatory lending practices and financing terrorism and corruption (Orol, 2018). In 2020, such practices have already been observed in Indonesia, where the Financial Services Authority shut down more than 1,000 unlicensed digital lenders that offered prohibited services and employed contentious debt collection approaches (Faux, 2020; Sahay et al., 2020). These trends could intensify during the pandemic given that millions of people have faced sudden job loss and unemployment. To mitigate these risks, there is a need for cross-sector partnerships at both the domestic and international levels for policy development (Sahay et al., 2020).

Stringent lockdown restrictions have also increased the over-reliance on AI for sustainable finance, which may lead to unintentional harms that foster exclusive inclusion. Due to the online-only nature of digital services, individuals without technological accessibility or literacy may be discriminated against and excluded. Unequal access to digital infrastructure, potential biases in data analytics and modelling, and lack of access to technology (e.g., smartphones, computers and the internet) could also lead to new forms of exclusion if there is a strong drive toward digital financial services during and after the pandemic (Sahay et al., 2020). Further, the pandemic could restrict already marginalized groups such as women, the elderly, those with disabilities, non-status migrants and those living in remote communities (UN, 2019b). Additionally, those experiencing homelessness, trafficked individuals (whose finances may be controlled or surveilled) and incarcerated individuals (who are forbidden to use electronic devices) would likely be excluded in a cashless society (Choi et al., 2021; Engert et al., 2018).

The COVID-19 pandemic is the first “natural experiment” event or test of resilience of AI for sustainable finance. To evolve governance objectives, cross-sector partnerships and multilateral activities must continue to be explored, including regulatory sandboxes that expose potential risks and benefits. Seminal reports such as the Bali Fintech Agenda have offered frameworks for AI for sustainable finance in the past, however, there still are no internationally agreed regulatory standards. The pervasiveness of the pandemic may very well have led to the reallocation of resources and priorities related to these ambitions. The silver lining is that, as the global community endeavours to navigate out of this natural experiment, AI for sustainable finance has once again answered the call to serve people and planet in times of crisis.

2.7 Key Considerations

While numerous journal papers, policy reports and grey literature have been published by scholars, governments, standard-setting and regulatory bodies, and private sector firms, few have investigated and incorporated findings of governance for AI for sustainable finance, from both societal and institutional vantage points. Although this proposal aligns with and complements earlier important works, including the 2020 report *The Promise of Fintech: Financial Inclusion in the Post COVID-19 Era* (Sahay et al., 2020), this chapter narrows the focus and disentangles concepts by providing three key policy recommendations when considering AI for sustainable finance. Drawing on findings from the literature, it is recommended that policy makers consider the following: first, mitigate unintended social and environmental consequences; second, promote ESG disclosure; and third, strengthen cross-sector partnerships.

Mitigate Unintended Social and Environmental Consequences

It is necessary to call on national governments, the private sector, intergovernmental organizations, and civil society to research, promote and implement AI for sustainable finance policies that respect social inclusion and environmental protection, using the SDGs as a framework. AI for sustainable finance must incorporate an inclusive, ethical and collaborative approach into its design, development and implementation. With the increased dependence on emerging technologies as a solution to development, both social and environmental implications must be considered.

First, inequitable social relations may appear between those who define, control and administer technology for development and the recipients of such solutions (Vinuesa et al., 2020a). These inequalities may ultimately violate the SDGs and, therefore, AI for sustainable

finance initiatives should consider who is included and excluded, who benefits and why, and how can the marginalized be empowered (Gupta & Vegelin, 2016). This entails an in-depth and critical understanding of the challenges faced by the present generations without compromising the livelihoods of future generations (P. (Tima) Bansal, 2019). Inclusion, feedback and input of end users are necessary ingredients that ensure value, consideration, agency and dignity for unbanked individuals (Dupas et al., 2018). As social, environmental and technological needs and constraints evolve, encouraging feedback from relevant stakeholders is important to ensure that AI for sustainable finance initiatives continue to add value to the user (Dupas et al., 2018). This input ensures that voices and changing circumstances are considered and that resources are effectively allocated to address them (Young, 2011).

Second, rapid innovation and greater access to technology have unintended consequences on the environment (WEC, 2019). The increased demands for energy that produce and fuel digital technologies have significant impacts on the environment in several ways, including increased resource mining, electricity usage, harmful byproducts, fossil fuel consumption and electronic waste (WEC, 2019). The WEC (2019) stated that electronic waste is the fastest growing waste stream globally, reaching 48 million tonnes and worth \$62 billion.

While much work is to be done, large organizations ('big tech') have recently started building sustainability programs to reduce and offset these implications (Rolnick et al., 2019). Technology giants such as Google have partnered with NGOs to shift toward circular economies by investing in restorative and regenerative data centres, products and supply chains (Google, 2020). Google has been carbon neutral since 2007 and for several years has been matching its energy usage with 100 percent renewable energy purchases (Google, 2020). The company has

also designed carbon-AI systems to shift heavy computing in their data centres during peak times using wind and solar power, without creating additional demands on electricity. This is part of an ambitious effort to source carbon-free energy on a 24/7 basis (Google, 2020). Despite this progress, big tech companies such as Google also contribute to climate change. For instance, Google's AlphaGo Zero AI project generated the same amount (96 tonnes) of CO₂ during its 40 days of training as 23 American homes (Wynsberghe, 2021). Not surprisingly, Amazon and Microsoft, despite promoting their sustainability efforts, also release large amounts of CO₂ emissions to run their services (Strubell et al., 2019).

Recipients or users of AI for sustainable finance should play a role in the design, development, and implementation of such innovations. This would ensure that various perspectives are considered equitably, which may increase adoption and enhance livelihoods (Gupta & Vegelin, 2016). Predicting the needs of future generations through sustainable development, therefore, is not against generating business wealth but addressing two unique and interrelated criteria: wealth should meet people's basic needs and should be generated within the constraints of the Earth's productive capacity (Bansal, 2019).

Promote ESG Disclosure

Stakeholders and markets are increasingly pressuring corporations, including financial services providers, to disclose details about their socio-ecological impacts via reporting (Elalfy & Weber, 2019). Amran et al. (2014) argue that reporting assists decision makers, namely, socially responsible investors, in processing environmental, economic and social data. Compared to 1999, there has been an increase in corporations (from 35 percent to 80 percent of the top 250 companies of the Global 500) producing reports, especially those who operate in "sensitive"

industries (e.g., resource extraction) (Amran et al., 2014). Reporting quality has and continues to face criticism surrounding the accuracy and transparency of ESG data. This has resulted in greenwashing and organizational biases that prevent concerned stakeholders from making effective and informed investment decisions (Eccles & Strohle, 2018). For instance, organizational leaders can control and disseminate information, withholding information to ultimately influence market performance (Eccles & Strohle, 2018).

AI for sustainable finance firms must be held to the same disclosure standards. Reports could include information about a firm's economic, environmental and social activities so that stakeholders can evaluate motivations, reputation and short- and long-term direction (Elalfy & Weber, 2019). ESG disclosure for AI for sustainable finance providers would also be a vital step forward to demonstrate transparency and effective governance as well as to enhance reputation and accountability. Such topics have recently entered mainstream discourse related to blockchain technology. Tesla CEO Elon Musk, a proponent of cryptocurrency, tweeted about Tesla halting the bitcoin as a payment method due to the exorbitant energy consumption of mining. Mining bitcoin is energy-intensive and typically relies on electricity generated by coal. Musk tweeted: "Cryptocurrency is a good idea...but this cannot come at great cost to the environment" (BBC, 2019). Soon after, Bitcoin's price plunged by 10 percent, and at one point a week later, it had dropped by 30 percent (down to \$34,770) (Browne & Kharpal, 2021). As a result, investors and public actors have come to know that mining bitcoin consumes more energy (121.36 terawatt-hours/year), and hence produces CO₂, than all of Argentina (121 terawatt-hours/year) (Criddle, 2021). Musk later signalled that Tesla would consider accepting payment through other cryptocurrencies that were less energy-intensive (Peterseil & Hajric, 2021). Subsequently,

bitcoin prices surged again when Musk tweeted that he met with the newly formed Bitcoin Mining Council that aims to “promote energy usage transparency & accelerate sustainability initiatives worldwide” (Michael_saylor, 2021). The sustainability case for business in this regard has the potential to incentivize fintech firms and investors alike toward ESG practices.

Strengthen Cross-Sector Partnerships

As the 17 SDGs and 169 associated targets are interconnected, the fulfillment of the 2030 Agenda will require sectors (including incumbents, start-ups, regulators and policy makers) to work collectively on financial resources, sharing of knowledge and technology, and tackling issues in all countries, especially developing ones (UN, 2019b). To support this aim, the United Nations can serve as a convener to explore the role, configuration and implementation of strategies that apply to AI for sustainable finance initiatives.

In both institutional and societal cases described in previous sections, experts from NGOs, the private sector, academia and government must come together to address sustainable development. This should be done with community members and end users contributing to solutions that will affect their livelihoods (Erdiaw-Kwasie & Alam, 2016). With this mindset, collaborations would allow each actor to identify and overcome existing gaps more effectively (Erdiaw-Kwasie & Alam, 2016). Global innovation systems have conventionally been created by single institutions in the private or public sectors, but have fallen short of meeting global targets, especially those addressing issues related to poverty, climate change and associated vulnerabilities (Casillas & Kammen, 2010; Eakin et al., 2014; Pinkse & Kolk, 2012). Typically, technologies are not developed for markets that do not drive revenue, or when developed, they do not consider the end user’s needs, lowering agency, adoption and efficacy (Anadon et al.,

2016). For instance, smaller fintech providers in Sub-Saharan Africa eagerly, but hesitantly, partner with larger incumbents as they often face power imbalances and fear that their businesses are at risk (Chetty et al., 2019).

During the COVID-19 pandemic, the integration of government digital systems and AI for sustainable finance firms proved effective in providing policy support in the absence of physical human interaction. Therefore, to ensure digital financial inclusion, a fiscal response must work in parallel with digital infrastructure implementation as well as enhance digital and financial literacy. Actors across sectors must strike a balance to ensure digital innovation can thrive while governance and regulatory mechanisms are in place as the demand increases for AI for sustainable finance. This will help prevent risks to financial integrity as well as to consumers (cybersecurity, predatory lending practices and so forth). Further, policy makers can work toward international standards and agreements on data privacy, cybersecurity, digital identification and digital currencies (Sahay et al., 2020).

AI for sustainable finance may present risks and contradictory, unintended or unexpected consequences. To effectively identify and manage the risks and opportunities related to AI for sustainable finance, there is a need for global dialogue and governance involving multiple stakeholders aligned with the SDGs. Partnerships (across and within sectors) and policies should be developed to share and bridge digital resources (data, knowledge, practices and tools) besides addressing topics with multiple lenses. This approach will aid in increasing standards consistency across institutions, digital equality and inclusion for underrepresented voices such as women and traditionally marginalized groups, and the interoperability of data and access for end users (UN, 2019b). Serving as an impartial facilitator, bodies such as the United Nations can

work with actors to develop AI for sustainable finance impact assessments and to ensure mechanisms that safeguard against data security and privacy issues (Hilbert, 2017). Other major areas requiring coordination include the lack of harmonized standards and interoperability of technology, fragmentation of payment systems, lack of commonly accepted application programming interface standards, and development of open-sourced platforms and a common payments ecosystem (Bank of International Settlements, 2019; Ehrentraud et al., 2020).

2.8 Conclusion

AI for sustainable finance is evolving rapidly. With its continued emergence, there will be both opportunities and risks related to sustainable development and financial stability that policy makers and regulators should consider. This chapter investigated the role and implications of AI in achieving the SDGs. To address current and future governance challenges, three key recommendations were provided to serve as a guidepost for AI for sustainable finance in both institutional and societal settings as well as through the COVID-19 pandemic. As with any innovation, AI can provide either opportunity or exacerbate social or environmental inequality, and responsibility falls on academics, policy makers, corporate actors, innovators, and citizens to work toward solutions beneficial to the three pillars of sustainability.

Building on the governance and policy perspectives outlined in Chapter 2, the following chapter turns to empirical analysis to examine how firms navigated the COVID-19 crisis. By comparing ESG ratings and AI-generated sentiment as proxies for stakeholder satisfaction, Chapter 3 evaluates their respective capacities to explain financial performance under conditions of systemic disruption. In doing so, it connects the systemic challenges of governance with firm-

level responses, providing evidence on how different measures of stakeholder orientation perform when subjected to crisis conditions.

MANUSCRIPT ENDS

3. AI-DRIVEN PUBLIC SENTIMENT VS. CONVENTIONAL ESG RATINGS: IMPACTS OF THE COVID-19 CRISIS ON STOCKS

The third chapter (July 2020 – June 2024) explores how AI-generated public sentiment data compare with conventional ESG performance data in offering material insights about the financial performance of Canadian firms during the COVID-19 pandemic. This is of interest as the relationship between ESG and financial performance remains of growing but mixed understanding in academia. Further, the nature of the relationship during a crisis remains to be fully understood, but some theoretical arguments have been suggested. With the COVID-19 pandemic, this area of research has begun to generate new empirical studies. However, from an empirical view, examining the relationship between ESG performance of firms during and post-crisis is a challenge due to the utilization of conventional ESG data. Further, the abruptness and speed at which the COVID-19 pandemic unfolded have not been captured in such ESG data. Thus, a recent development in the measurement of ESG performance has been the use of AI-generated public sentiment ratings.

This chapter contributes to theory by testing the efficacy of conventional ESG as a social innovation (in the wake of the pandemic) against (Westley, 2014, para. 1) definition. Findings show that conventional ESG data (during such crises) do not meet aspects of this definition (e.g., durability and scalability), whereas AI-generated public sentiment data does.

3.1 Introduction

The coronavirus disease 2019 (COVID-19) pandemic is the most devastating and pervasive challenge in modern history. At its worst, COVID-19 undermined the resiliency of our healthcare systems and livelihoods in addition to financial markets, economies, and businesses worldwide. In the finance sector, the pandemic and subsequent impacts of COVID-19 came as a shock to investors (Ramelli et al., 2020). Investors rely on environmental, social, and governance (ESG) insights to measure a firm against sustainability criteria to help support their investment strategies and decisions. At a microeconomic level, the dynamicity of the pandemic caused severe disruption in areas such as labour, supply chain, consumer spending and affordability (Fornaro & Wolf, 2020). There remains a dearth of understanding of how firms respond during severe economic meltdowns, and how firms adjust their limited resources during the market crash and the following rally. The market environment during the COVID-19 pandemic offered a natural experiment through which to understand ESG performance in a resource-constrained economy (Albuquerque et al., 2020). The primary function of ESG scores is to capture non-financial performance, as accurately as possible, so that stakeholders can evaluate companies and that companies can understand how to respond and adapt to material global events (Kotsantonis & Serafeim, 2019). In times of crisis, investors rely on financial and non-financial information to reduce risk and maximize or maintain profits (Hoffmann et al., 2013). During such periods, material insights from ESG information can help investors identify firms with 'good' management practices, which may deliver superior financial performance and effectively mitigate risks during periods of volatility (Waddock & Graves, 1997). However, recent studies

have shown that conventional ESG scores do not accurately capture the dynamic nature of crises such as the COVID-19-related risks that businesses may face (Cardillo et al., 2023; Demers et al., 2021).

Empirically, examining the relationship between ESG performance of firms during crises is a challenge due to the utilization of conventional ESG data. Specifically, there are three main challenges to consider. First, studies examining the COVID-19 financial crisis often used ESG ratings generated before the pandemic, which may not accurately reflect the pandemic-specific variables and impacts on firm performance (Folger-Laronde et al., 2020). Such data are static as they are generated annually or quarterly. Second, recent works have criticized the methods and data used in early COVID-19 studies that supported ESG performance as a resilience factor, suggesting that ESG is “incrementally insignificant” after controlling for accounting-based measures (Demers et al., 2021, p. 2). Third, the speed and dynamic nature at which the COVID-19 pandemic unfolded have not been captured in such ESG data.

A recent development in the measurement of ESG insights has been the use of AI-generated public sentiment ratings from alternative sources such as news media, think tanks, social media, non-governmental organizations (NGOs), and academic journals related to company ESG performance (Serafeim, 2020). We join the small but growing number of scholars (e.g., Eccles & Strohle, 2018; Serafeim, 2020) who examine public sentiment to gain an understanding of its relationship to financial performance (Eccles, 2020; Kuh et al., 2020). While other studies have examined the financial markets during the COVID-19 outbreak, to our knowledge this paper is the first of its kind to examine the relationship between ESG

performance and financial performance in Canada, using public sentiment ratings generated by AI.

This research used a good management theory lens (Waddock & Graves, 1997) to explore the relationship between financial and non-financial performance of Canadian firms during the COVID-19 pandemic. Through this lens, it was possible to gain insights into dynamic materiality, a concept that recognizes the fluid nature of investors' perceptions about which material ESG issues matter most in the context of market volatility and complex global challenges (Eccles, 2020). While Waddock and Graves' (1997) expressed corporate social performance as a proxy for stakeholder relations, we adapt their notions by suggesting that public sentiment and ESG performance are proxies for stakeholder satisfaction. Further, we draw on Busch et al.'s (2018) notions of value creation to define stakeholder satisfaction as the extent to which stakeholder expectations and needs (i.e., financial risk mitigation, innovation, ethical practices) are fulfilled by a firm. This definition also aligns with findings from Waddock and Graves' (1997) research, which indicate that effective stakeholder relations correlate with enhanced financial performance, and thus, it is in the best interest of managers to maximize stakeholder value (Freeman et al., 2004). Accordingly, we asked, how does AI-generated public sentiment data compare with conventional ESG performance data in offering material insights about the financial performance of Canadian firms during the COVID-19 pandemic? This relationship remains a growing question in the literature. The nature of this relationship during a crisis is not fully understood, although some theoretical arguments have been suggested.

We employed cross-sectional models and random effect panel analysis. For each, the dependent variable is financial performance using abnormal return or stock price volatility. The

independent variables are the public sentiment and ESG measurements. Public sentiment ratings are provided across five COVID-19-related categories (labour, supply chain, response, economy, and social impact) as determined by Truvalue Labs.

Findings of this study offer several contributions to the literature and industry stakeholders. First, we contribute to good management theory by providing a more nuanced understanding of dynamic materiality, which demonstrates the relationship between a firm's stakeholder satisfaction efforts and its financial performance. The public sentiment data allow for more timely insights into changing stakeholder perceptions and market behaviour, however, has not been represented or considered in previous empirical studies. This contribution helps address Demers et al. (2021, p. 22) question about “whether doing good is good for investors” in times of crisis. Second, this study offers methodological contributions by using novel methods to examine how AI-generated public sentiment ratings compare to conventional ESG ratings in offering material insights. While prior ESG studies have used AI-generated data, our study is particularly useful to researchers and practitioners as it measures multiple COVID-19-related signals and sub-signals every week. Third, our study is the first of its kind to examine the relationship between ESG and financial performance of Canadian firms during the pandemic. While prior studies have carried out empirical research about firms in the US, Europe, and G20 countries in the context of the pandemic, to our knowledge, none have offered unique insights or implications about how well Canadian ESG performers fared during the crisis in 2020.

This paper is organized as follows: Section 2 describes the related literature and highlights the theoretical framework; Section 3 explains the methodology and the data used for our main

tests; Section 4 introduces the descriptive and exploratory statistical data analyses conducted; Section 5 presents a discussion on the results, and Section 6 reports our concluding remarks.

3.2 Literature Review

ESG and Financial Performance in Times of Crisis

From many decades of empirical research, the prevailing view of superior ESG-performing firms is that they generate positive financial performance for their investors (Folger-Laronde et al., 2020). While early critics (e.g., Friedman, 1970) and empirical work suggested that ESG performance is costly to investors (Adler & Kritzman, 2008; Hylton, 1992), notable studies have found evidence suggesting a slight positive relationship between ESG and financial performance (Friede et al., 2015; Orlitzky et al., 2003). The value creation from superior ESG performance can be generated in a variety of forms: good management, risk management, regulatory protection, and stakeholder satisfaction (Heal, 2005; Henisz & McGlinch, 2019). Empirically, studies have found that financial performance positively affects ESG performance and ESG performance positively affects financial performance, lending credence to good management theory (Orlitzky et al., 2003; Waddock & Graves, 1997). For instance, Waddock and Graves (1997) explored the direction of causation between ESG performance and financial performance. However, the accumulating empirical primary and meta-analyses on the nexus of these variables have led to increased attention and examination of the relationship between ESG and financial performance during crises.

The nature of the ESG-financial performance relationship during a crisis remains to be fully understood (i.e., saving through the crisis, dropping ESG activities, etc.) (Bansal et al., 2015). Specifically, it is unclear whether managers during crises would decrease, sustain, or

increase their allocation of resources towards ESG activities, and how these activities relate to, or impact financial performance. Prior literature has also shown that E, S, and G factors respond differently in times of crisis. The relationship between corporate governance (G ratings) and performance during times of crisis has been a particular topic of interest for many researchers since the 2008 GFC (Folger-Laronde et al., 2020). Prior works that studied the 2008 GFC suggested that the importance of governance was overshadowed by market conditions and macroeconomic factors (Lee et al., 2017), and did not provide a protective effect (Dahya et al., 2013; Durnev & Kim, 2005). Van Essen et al.'s (2013) notable study sampled 1,197 firms across 26 European countries and examined how good governance influenced firm performance in non-crisis and crisis periods. Their findings showed that governance mechanisms function differently during non-crisis and crisis times and that stringent measures during crises may be counterproductive as they limit managerial ability and agility. More recently, Ding et al. (2020) examined 6,200 firms across 61 countries and found that management with less director entrenchment experienced less volatility in stock returns. In contrast to high G firms, high E and S firms have experienced enhanced financial performance (Albuquerque et al., 2020; Engelhardt et al., 2021; Lins et al., 2017). For instance, Garel and Petit-Romec (2021) found a positive association between environmental scores and stock returns during the pandemic, suggesting investor sentiments in favour of climate action and environmental risk mitigation. A notable study by Lins et al. (2017) showed that firm-specific social capital served as an 'insurance policy' in times when investors lost confidence in them. They found that firms that exhibited superior ES ratings had better financial performance during the GFC and found no statistical difference in stock return performance during the recovery phase, post-crisis (Lins et al., 2017).

The understanding of the relationship between high G ratings and financial performance during the pandemic period is understudied.

The COVID-19 pandemic created uncertainty as to what the relationship between ESG and financial performance would look like, which has generated new studies. While initial research suggested that ESG performance was positively related to financial performance during the COVID-19-induced crash, more recent studies point to a mixed or inconclusive relationship. Prior and recent literature (Demers et al., 2021; Opler & Titman, 1994; Ramelli & Wagner, 2020) have suggested that accounting-based variables (i.e., leverage, liquidity, supply chain management) offer important clues into organizational behaviour, performance, and resilience resulting from crises. Indeed, Demers et al. (2021) argued that such factors, rather than ESG, provide valuable insights about financial performance during crises.

Empirical Challenges in Examining ESG in Times of Crisis

From an empirical view, a major challenge when examining ESG in times of crisis, and central to this research study, is the measurement of ESG performance. The use of ESG ratings as a proxy for ESG performance has long been debated in empirical studies (e.g., Friede et al., 2015; Orlitzky et al., 2003), particularly given prior and recent works resulting in mixed findings. The primary approach in prior empirical literature (Cahan et al., 2015; Ghoul et al., 2011) was to employ the use of static (annual) ratings when trying to relate changes in a firm's ESG performance to financial performance (Schmidt, 2019). This cadence does not enable scholars to capture the dynamic nature of crisis events in their works, in a timely manner. Turning to ESG funds for instance, Corporate Knights ESG ratings and financial returns of Canadian equity exchange-traded (between pre-COVID-19 and during COVID-19) showed

that the links between these ratings and business resiliency appear to be weakest (Folger-Laronde et al., 2020). This suggests that conventional ESG data are not able to capture ESG performance in times of turmoil because they do not address the resiliency of investments. Resiliency refers to the ability of investors to anticipate, avoid and adapt to changing conditions after external shocks without losing their primary function, structure, and identity (Bae et al., 2021; Ortiz-de-Mandojana & Bansal, 2016).

Further, Eccles and Strohle (2018) argue that despite the growing appetite for data and empirical evidence showing a correlation between ESG performance and financial outcomes, the field remains unorganized and without universally agreed-upon measurement standards. With over 100 data providers in the ESG rating ecosystem, there remains a lack of transparency concerning the rating methodology, which is magnified by unstandardized metrics, indicators, and methods. This has created a variance in ratings and recommendations that potentially confuse and misinform investors but also lead to different outcomes in academic research (Eccles & Strohle, 2018; Folger-Laronde et al., 2020). Concerning the latter, researchers must be careful in selecting ESG data purveyors as insights about the ESG and financial performance relationship from one vendor may not be replicable with data from another (Berg et al., 2022). Relatedly, Berg et al. (2022) found that divergence in results was very common for MSCI ESG Stats data (formerly KLD Stats) – the data used for most academic research. Other studies (e.g., Chatterji & Toffel, 2010; Delmas et al., 2013) have also cautioned researchers, stakeholders, and policymakers alike when drawing conclusions about ESG performance.

Another challenge when examining ESG in this context is that financial crises and health pandemics are quite rare. Although there have been various economic downturns and health

pandemics across the globe, before COVID-19, the most severe had been the Great Depression of 1929 and the GFC of 2007-2009 (Flammer & Ioannou, 2021). The unprecedented and swift impacts of the COVID-19 pandemic led to an increasing collection of empirical studies that have examined the role of ESG performance during the initial financial crash and the subsequent recovery. In the recent empirical research under a COVID-19 context, we highlight three main weaknesses with the use of ESG ratings. First, most studies utilize ratings generated before the pandemic (i.e., 2018 ESG ratings). Therefore, annual ESG ratings may not provide accurate material insights into the ESG-related strategies and activities that managers may follow during a crisis. Second, there is a concern about the ability of ESG ratings to capture social indicators such as the responsiveness of firms during a health crisis toward their workforce or local communities, as indicated by Folger-Laronde et al. (2020). Third, despite the widespread results and conclusions (i.e., claiming ESG was a resilience factor) of some preliminary COVID-19 studies, concerns about replicability and accuracy have been raised when considering the data, sample, control variables, and measurements that were selected (Demers et al., 2021).

Theoretical Framework: Good Management Theory During a Global Crisis

During crises, corporate responses are multifaceted, exhibiting both challenges and opportunities, influenced by endogenous and exogenous sources of volatility (Flammer & Ioannou, 2021). While the link between ESG performance and financial performance is well documented during non-crisis contexts, there is a dearth of theoretical underpinnings specifically for the crisis context. Some works have taken a theoretical approach to interpreting their findings using crisis theory (Al Amosh & Khatib, 2023), stakeholder theory (Chiaramonte et al., 2022; Velte, 2017), and institutional theory (Riaz, 2009). However, research on the COVID-19

pandemic has generally overlooked theoretical perspectives that are essential for distinguishing between static and dynamic materiality. The lack of a theoretical foundation complicates the interpretation of findings, and thus, calls for a more nuanced approach that examines such differences (Al Amosh & Khatib, 2023; Pizzi et al., 2023). In response, we developed a theoretical framework that applies a crisis lens to Waddock and Graves' (1997) conceptualizations of good management theory, which regarded corporate social performance as a proxy for stakeholder relations. Further, we propose two lenses that investors can examine a firm's ESG-related behaviour: the first lens utilizes public sentiment, indicative of dynamic materiality, while the second focuses on ESG performance, representative of static materiality. Both serve as proxies for evaluating stakeholder satisfaction. This approach enhances our understanding of the evolving nature of management-stakeholder relations during crises and presents a unique opportunity to examine whether AI-generated public sentiment data can address the constraints observed in prior COVID-19 studies that relied solely on conventional ESG data.

Good Management Theory

Good management theory, a nuanced articulation of stakeholder theory, suggests that firms with effective management practices (i.e., returns to shareholders, innovation, diversity, and stakeholder management) tend to exhibit better ESG performance, leading to overall improvements in financial performance (Waddock & Graves, 1997). This virtuous cycle results in enhanced competitiveness, reputation, stakeholder satisfaction, access to capital, and the ability to attract top talent (Orlitzky et al., 2003). Therefore, ESG performance becomes both a

predictor and a consequence of firm financial performance, establishing a contemporaneous and bidirectional relationship (Orlitzky et al., 2003; Waddock & Graves, 1997).

Good management practices during severe economic crises are a contentious topic, due to disparate stakeholder expectations. Leaders (i.e., board directors and managers) are called upon to make ‘good’ decisions that either result in doing what is (morally) right or doing what is (economically) best. Some argue that firms may need to cut costs, such as laying off employees or reducing community investment, during economic downturns to weather the crisis (Bansal et al., 2015; Flammer & Ioannou, 2018). During the GFC for example, firms responded by significantly reducing their capital expenditures and enforcing layoffs (Flammer & Ioannou, 2021). Some investors may view externalizing costs to society as necessary for firms to survive and consider cash reserves highly valuable for companies facing difficulty accessing external capital (Ramelli & Wagner, 2020; Shleifer, 2004). This was especially true for firms with limited cash holdings and high leverage during the COVID-19 pandemic (Ramelli & Wagner, 2020). However, Nemlioglu and Mallick (2021) argue that firms with good management practices utilized their leverage and innovation to safeguard and enhance their financial performance during the pandemic, emphasizing the importance of investing in workers and the community as a means of increasing resilience (Flammer & Ioannou, 2018). Accordingly, notions about good management practices, particularly during crises, are complex and are not fully understood in the pandemic context.

To forge meaningful intersections between those who value moral considerations (doing what is right) and those who prioritize economic ones (doing what is best) during crises, this study extends the application of good management theory and redefines ‘good’ in two important

ways. First, firms can better weather economic shocks by concentrating their governance efforts on essential crisis mitigation and management activities. Corporate directors should emphasize acquiring slack resources during periods of stability and strategically deploying them when needed to absorb shocks, support long-term sustainability strategies, and appoint skilled managers to ensure effective stakeholder management. In this regard, Flammer and Ioannou (2021) provide three approaches to enhance stakeholder satisfaction, and hence, strengthen their financial performance: 1) reduce short-term liabilities and ‘save their way’ out of the pandemic, 2) exploit volatility by hiring new employees at lower rates or invest in ESG to enhance competitiveness, or 3) simultaneously reduce short-term liabilities and increase ESG activities (Flammer & Ioannou, 2021).

Second, corporate directors can incorporate crisis response strategies with broader governance frameworks to ensure managers can swiftly deploy available slack resources and prioritize economic responsibility (Carroll, 2016). Notably, risk management committees, as suggested by (Jebran & Chen, 2021), could be instrumental in implementing such strategies during crises that accommodate dynamic materiality (Kuh et al., 2020). The integration of good management practices such as strategic agility and adaptive governance enables firms to establish a protective ‘insurance’ mechanism that helps reduce volatility and enhance financial returns (Ding et al., 2020; Waddock & Graves, 1997). As a result, crisis-flexible governance mechanisms can contribute to stakeholder satisfaction and long-term profitability (Jin et al., 2022). This aligns with Graves and Waddock's (1999) findings that the quality of management and the quality of stakeholder relations function as parallel measures of financial performance.

AI-Generated Public Sentiment Ratings: A Proxy for Stakeholder Satisfaction

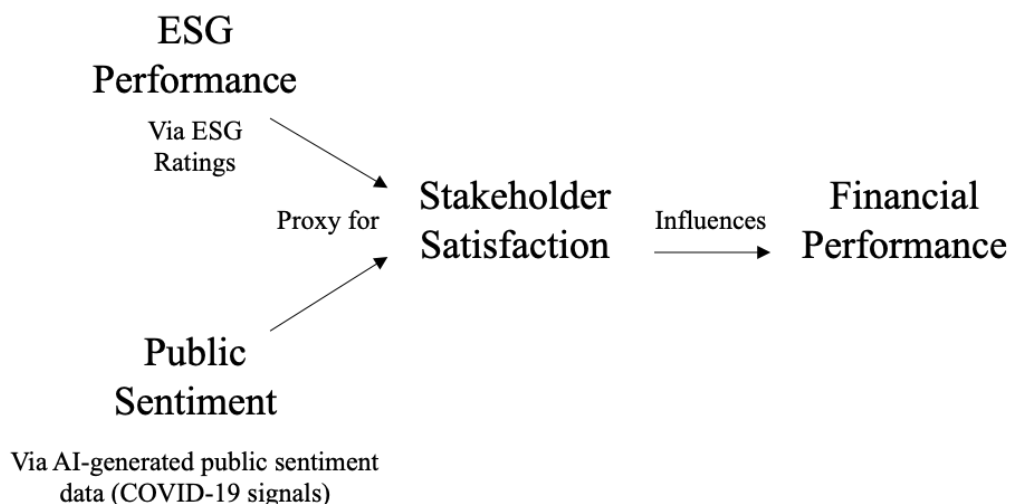
In times of crisis, it is the main function of ESG ratings to capture firm performance, as accurately as possible, so that stakeholders can evaluate companies and that management can understand how to respond to unfolding events (Kotsantonis & Serafeim, 2019). However, investment strategies typically do not rely on day-to-day news but rather on static (annual or quarterly) ratings of firms when incorporating ESG issues during decision-making (Schmidt, 2019). This presents a challenge when considering the rapidly changing landscape of events as well as the probable speculative behaviour and sentiment of investors (Black, 1986; Schmidt, 2019). As such, the abruptness and speed at which the COVID-19 pandemic unfolded, and how it affected stakeholder satisfaction, have not been captured in such static ESG ratings.

Prior studies (e.g., Cheong et al., 2017; Krüger, 2015) examining ESG-specific sentiment and financial performance have shown that stakeholders articulate and react strongly to positive and negative news, suggesting that stakeholders are critical to influencing ESG materiality (Kuh et al., 2020). The growth of finance and ESG research in the wake of big data and emerging technology has prompted scholars to explore tools generated by AI. Such tools use unstructured big data to generate scores to enhance decision-making (Macpherson & Gasperini, 2021; Serafeim, 2020). This development in measuring and understanding ESG performance relies on AI-generated public sentiment ratings. These techniques are used to capitalize on early risk identification and emerging opportunities for investing (Pashang & Weber, 2023). Unlike conventional ESG ratings, AI-generated ratings incorporate public sentiment from 100,000+ sources related to a firm's weekly ESG activities (Serafeim, 2020). Findings from one study that investigated over 3000 firms globally indicated that firms with more positive public sentiment

surrounding their response to COVID-19 experienced lower negative returns than their counterparts during the market collapse in 2020 (Cheema-Fox et al., 2020). Public sentiment ratings could offer both complementary ESG measurements during business-as-usual times, as well as added insights during crisis times when timelier ESG measurements are needed.

Thus, in the context of good management theory, an interesting research avenue emerges - examining how AI-public sentiment ratings can be used as a proxy for stakeholder satisfaction. This inquiry prompts an examination of the comparative merits between AI-public sentiment data and conventional ESG ratings as seen in Figure 1. As such, our study examines these factors to provide novel insights into crisis-induced market crashes.

Figure 3-1 ESG Performance and Public Sentiment as Proxies for Stakeholder Satisfaction



Note: This figure illustrates the conceptual model where ESG performance and public sentiment are used as proxies for stakeholder satisfaction. ESG performance is measured through ESG ratings, while public sentiment is captured via AI-generated data, particularly considering COVID-19 signals. This figure suggests that stakeholder satisfaction, represented by these proxies, impacts the financial performance of firms. Source: Author.

3.3 Data and Methodology

Sample and Summary Statistics

This study used a combination of non-financial and financial data for Canadian firms to conduct statistical analysis. The two non-financial data sources are AI-driven COVID-19-related public sentiment ratings from Truvalue Labs (TVL) (now part of FactSet) and ESG ratings from Refinitiv. The market and accounting variables were sourced from Compustat. After matching the three databases, the total sample size is 236 Canadian firms. The decision to focus on Canadian firms responds directly to a significant gap in the existing literature. Much of the empirical research on the relationship between ESG performance, financial performance, and crisis dynamics has concentrated on U.S. firms or broader G20 markets (e.g., Cheema-Fox et al., 2020; Albuquerque et al., 2020). To date, few studies have examined this relationship in a Canadian context, despite the country's distinct institutional environment and substantial fiscal intervention during the COVID-19 pandemic. This absence of Canada-focused analyses leaves an important gap in understanding how sustainable finance mechanisms operate outside of the more frequently studied U.S. and global contexts. We further drop all financial and real estate firms from our main tests, leading to a sample of 176 Canadian firms for the primary dataset. Financial and real estate firms were excluded from the sample because their business models and capital structures differ substantially from those of the broader economy. Banks and real estate companies are highly capital-intensive, heavily regulated, and deeply tied to the financial system. Their returns and risk exposures behave very differently from other sectors, particularly during times of crisis, which would have reduced the comparability of results. Including these sectors would also have introduced potential bias, as their sheer size and systemic role could dominate

the results and mask the dynamics under examination. By removing them, the analysis creates a cleaner sample that more effectively isolates the relationship between ESG performance, fiscal stimulus, and the financial performance of non-financial firms. This approach is consistent with prior ESG–COVID research, such as Demers et al. (2021), who excluded financial and real estate firms for precisely these reasons. To study the impact of stakeholder satisfaction on corporate financial performance during the COVID-19 crisis and compare the utility of conventional ESG ratings and AI-driven public sentiments in measuring stakeholder satisfaction in this relationship, we employ two sets of regressions. The first set uses cross-sectional ordinary least squares (OLS), and the second set uses random effect panel analysis.

Refinitiv ESG Data

The conventional ESG ratings are sourced from Thomson Reuters Refinitiv ESG data for 2019. This database produces scores based on over 600 ESG-related metrics using publicly reported data. The ESG scores used in this study are the overall ESG-composite (ESG), the Environmental Pillar (ENV), the Corporate Governance Pillar (GOV), and the Social Pillar (SOCIAL). Firm-level ESG performance is assessed annually based on industry materiality and scored relative to sector peers. To provide one of the proxies for stakeholder satisfaction, we used continuous scales, from 0 to 100, with higher scores indicating higher performance. Refinitiv ESG ratings have been widely used in prior literature, including studies by Albuquerque et al. (2020) and Demers et al. (2021).

Truvalue Labs COVID-19 Sub-signals

AI-generated data vendors like TVL analyze public sentiment from sources such as news media, think tanks, social media, non-governmental organizations (NGOs) and academic journals related to company ESG performance (Serafeim, 2020). Using natural language processing (NLP) and machine learning techniques, TVL aggregates (100,000+ data sources), extracts (4.5 million data points), and analyzes (300,000 signals) unstructured big data and incorporates the Sustainability Accounting Standards Board's (SASB) 30 materiality classifications to generate scores (0–100) (FactSet, 2023; Serafeim, 2020). Truvalue Labs' public sentiment ratings have been used in prior literature, such as studies by (Q. Li et al., 2024; Serafeim & Yoon, 2022).

During the COVID-19 pandemic, TVL produced public sentiment scores across different sub-signals (themes) at the firm level for weeks starting on 2020-01-08. To achieve this, multiple algorithms were built to capture media mentions of COVID-19 concerning firms, which were then assessed for public sentiment. Unlike prior research that uses TVL (e.g., V. Z. Chen, 2020), the COVID-19-related public sentiment database, seen in Table 1, comes with the following sub-signals: labour, supply chain, response, economy, and social impact (Truvalue Labs, 2020b). The COVID-19 sub-signals are scored based on a -20 to +20 range with 0 being neutral. We also constructed a net measurement of all five sub-signals (netSignals) by adding all scores per firm per week. The sub-signal data was provided as weekly observations per firm, starting on Wednesdays to the following Tuesday. This study has weekly observations for the weeks starting January 8th, 2020, to September 9th, 2020, for a total of 36 weeks. It is important to note that not all firms had observations for each week.

This dataset covers a significantly longer period compared to prior works (e.g., Cheema-Fox et al., 2020), which included public sentiment observations only during the weeks of the COVID-19 market crash from February to March 2020. By utilizing weekly public sentiment ratings over an extended period, this study provides a more comprehensive view of stakeholder satisfaction with a firm’s activities related to the COVID-19 pandemic. This novel approach allows for deeper investigation into good management theory, as the weekly observation basis of public sentiment serves as a dynamic proxy. Specifically, this additional information highlights the importance of dynamic materiality during a crisis, offering nuanced insights that static data (i.e., conventional ESG ratings) cannot capture.

Table 3-1 COVID-19 Sub-signal Definitions

Labour	employees, layoffs, working from home, paid sick leave, unemployment, and related topics
Supply Chain	supply of goods, production halts, manufacturing stoppages, and other related
Response	Research and development (R&D) or efforts to create vaccines or to shift manufacturing to produce test kits, ventilators, sanitizer, or any other unusual, crisis-specific goods, services, or products
Economy	broader economy
Social Impact	quality of living, access to education, social distancing, mental health, depression, access to healthy food, and related topics

Note: Adapted from “Truvalue Labs Coronavirus ESG Monitor Data Dictionary – For Clients” by Truvalue Labs, p.1. Copyright 2020 by Truvalue Labs (A FactSet Company).

Corporate Financial Performance Variables

Two broad dependent variables are used in this study, where there are specifications for the cross-sectional regressions and then for the panel analysis. Canadian firm stock and the index prices (S&P/TSX Composite Index) were sourced from Compustat. First, for returns in the cross-sectional regressions, buy-and-hold abnormal returns (BHAR) from January 8th, 2020, to the end of the week starting September 9th, 2020. For a range-based risk measurement, the median of weekly price ranges (weekly high minus weekly low) scaled by the midpoint was used. With TVL's public sentiment data being expressed on a firm-week basis (Wednesday to the following Tuesday), for the panel analysis we chose to construct the corporate financial performance measurements also on a weekly basis to provide a more consistent comparison. For the return measurement, we used weekly abnormal return, which is the weekly (Wed-Tues) sum of daily abnormal returns, where the capital asset pricing model (CAPM) beta is estimated using weekly (Wed-Tues) returns from 2019. While multi-factor models such as Fama–French are frequently employed in long-run asset pricing studies, they are less reliable during crises. Factor estimates often become unstable under extreme market conditions, reducing their interpretive value. By contrast, CAPM provides a transparent and straightforward benchmark that effectively controls for market-wide movements in short-horizon, event-driven settings. This approach is also consistent with prior COVID–ESG studies, such as Albuquerque et al. (2020), which enhances comparability with the emerging literature. Although CAPM may appear less complex, in the context of a global crisis it offers greater robustness and clarity. When considering stock price volatility, we used weekly price range (weekly high price minus weekly low price), scaled by the midpoint, again from Wednesday to the following Tuesday. The rationale is that range-based

measures capture the extremes of market movements, which are particularly salient during crises when tail risk dominates investor behaviour. Standard deviation, by contrast, smooths out volatility and underrepresents the magnitude of sharp swings. The high–low range provides a model-free measure that does not rely on distributional assumptions about returns, an advantage under stressed market conditions.

Control Variables

In all the statistical analysis, we employed the following control variables for each Canadian firm in our sample, Tobin’s Q, size, cash, leverage, return on equity, historical volatility, and dividend yield. The data for the control variables for 2019 was sourced from Compustat. To control extreme values, we Winsorized all control variables at the 1% level in each tail. The definitions for all variables used in this study are provided in the Appendix. Both the cross-sectional and panel analyses consisted of 176 unique Canadian firms, with the panel dataset having 3,242 firm-week observations. Table 2 presents summary statistics.

Table 3-2 Summary Statistics

	Observations	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Dependent Variables:						
Financial Performance						
BHAR	175	0.177	1.278	-0.218	0.031	0.362
MedianScaledRange	175	0.044	0.018	0.027	0.046	0.059
WeeklyAbnormalReturn	6,336	-0.055	9.985	-3.782	-0.071	3.577
WeeklyPriceRange	6,336	8.03	8.196	3.213	5.699	9.877
Independent Variables:						
ESG Ratings (2019)						
ESG	175	0.444	0.2	0.27	0.447	0.598
ENV	175	0.357	0.264	0.129	0.333	0.557
GOV	175	0.552	0.224	0.373	0.574	0.732
SOCIAL	175	0.439	0.225	0.251	0.4	0.605
Accounting Controls (2019)						
TobinsQ	175	1.682	1.225	1.014	1.313	1.779
size	175	6.322	2.485	5.57	6.886	7.948
cash	175	0.1	0.164	0.012	0.039	0.108
leverage	175	0.282	0.196	0.125	0.276	0.407
ROE	175	0.037	0.226	-0.046	0.054	0.135
dividend	175	1.964	2.458	0	1.042	3.385
historicalVolatility	175	0.054	0.029	0.031	0.052	0.068
Public Sentiment on COVID-19						
netSignals	3,233	-0.749	3.234	-2.401	-0.631	1.067
labour	1,229	-0.7	1.083	-1.276	-0.644	-0.043
supplyChain	1,465	-0.625	1.218	-1.2	-0.57	0.021
response	778	-0.323	1.344	-1.038	-0.278	0.406
economy	2,981	0.747	1.917	-0.471	0.4	1.688
socialImpact	2,520	-1.04	0.924	-1.505	-0.975	-0.539

Note: This table reports the summary statistics (number of observations, mean, standard deviation, and 25th, 50th [median], and 75th percentiles) for all variables. Table A1 in the appendix defines all variables used in the paper

Empirical Design

To answer our research question, two sets of regression were employed. First, we employed a cross-sectional OLS regression to identify the relationship between stakeholder satisfaction and corporate financial performance at an aggregate level across a 36-week time span. Within these cross-sectional studies, we have specifications using two alternative proxies for stakeholder satisfaction: ESG ratings or AI-generated COVID-19 public sentiment ratings. The objective of employing two sets of cross-sectional regressions was to compare the ability of the alternative proxies to capture the relationship between stakeholder satisfaction and the dependent variable of financial performance. Specifically, we aimed to identify which measure of stakeholder satisfaction provides a more robust and insightful model at the cross-sectional scale. To investigate more on the effectiveness of the COVID-19 public sentiment measure for stakeholder satisfaction, we employed random effects panel models.

The second type of regression we used are random effects models, where the panel data is structured by firm-week observations. The panel regressions did however not include the ESG ratings proxy measure for stakeholder satisfaction because as a time-invariant variable, including it with the other time-invariant control variables would lead to multi-collinearity. The random effects panel regressions allow for an examination of the time-varying effect of stakeholder satisfaction during the COVID-19 pandemic when measured by COVID-19-related public sentiment and thus capture the time dynamics of this proxy's impact on the weekly financial performance variable.

For the cross-sectional linear regressions, the following specification was used:

$$\begin{aligned}
& \text{Financial Performance}_i \\
& = \beta_0 + \beta_1(\text{Stakeholder Satisfaction})_{i,k,l} + \beta_2(\text{Firm Controls})_i \\
& + \beta_3(\text{Industry})_i + \varepsilon_i
\end{aligned}$$

Where i is the ith firm, k is for the proxy measurement for stakeholder satisfaction (ESG ratings or COVID-19 public sentiment), and l is for the lth ESG rating (ESG, ENV, GOV, SOCIAL), or for the lth COVID-19 public sentiment (aggregate, labour, supply chain, response, economy, social impact). The two dependent variables for the cross-sectional regression are BHAR and median weekly price ranges, which were calculated as an aggregation across the 36 weeks of the study's time span. Further, while the ESG rating proxy for stakeholder satisfaction is time-invariant, we were still interested to see the aggregate effect of the public sentiment ratings. So, we averaged the five sub-signals and netSignals per firm to include this proxy in the cross-sectional models. Included in the cross-sectional models are also several firm-specific characteristics (Tobin's Q, Size, Cash, Leverage, Return on equity, Historical volatility, and Dividend yield), as well as industry dummies. The control variables and industry variables are time-invariant variables, calculated from the 2019 period. The standard errors are robust to heteroscedasticity.

The second statistical tool used studied the time-varying effects of the COVID-19 public sentiment ratings on weekly financial performance. These random effects panel regression model is expressed as follows:

$$\begin{aligned}
& \text{Financial Performance}_{i,t} \\
& = \beta_0 + \beta_1(\text{Stakeholder Satisfaction})_{i,k,l} + \beta_2(\text{Firm Controls})_i \\
& + \beta_3(\text{Industry})_i + \alpha_i + \varepsilon_{i,t}
\end{aligned}$$

Where i is the i^{th} firm, t is for t^{th} week, k is for the k^{th} COVID-19 public sentiment theme (netSignals, labour, supply chain, response, economy, social impact). The two dependent variables were weekly abnormal financial returns and weekly price range for the 36 weeks, measured starting Jan. 8th, 2020, to Sept 9th, 2020. We controlled various firm characteristics: Tobin's Q, Size, Cash, Leverage, Return on equity, Historical volatility, and Dividend yield of firm i in 2019. Standard errors are clustered by firm to allow for heteroscedasticity and serial correlation.

In this study, a random effects panel model methodology was chosen over a fixed effects model for two primary reasons. First, the Hausman test conducted to assess the appropriateness of the random effects versus fixed effects specification indicated that the individual-specific effects were uncorrelated with the explanatory variables included in the model ($p\text{-value} = 0.54$). Second, the reason to use a panel methodology was to investigate the within-unit variation of the time-varying variables (i.e., COVID-19-related public sentiment ratings), rather than the within-unit variation of the time-invariant control variables. Taken together, the results of the Hausman test and the focus on examining the within-unit variation of time-varying variables led to the selection of the random effects panel model. In combination, we intended to use the advantages of both types of regression models. The cross-sectional model enables an aggregate analysis, while the random effects panel model enables an investigation into the time dynamics of the AI-generated public sentiment ratings as a proxy for stakeholder satisfaction.

3.4 Results

To address our research question regarding how ESG insights derived from AI-generated public sentiment data compare with conventional ESG ratings of Canadian firms during the

COVID-19 pandemic, we employed cross-sectional models and random effect panel analysis. With our aim to investigate the relevance of dynamic materiality during the COVID-19 pandemic, where conventional ESG ratings are limited in this regard compared to the weekly AI-generated public sentiment scores, using both regression approaches allows for a complimentary approach. The cross-sectional analysis allowed us to incorporate the time-invariant ESG ratings from 2019 but also enabled us to conduct an aggregate analysis of this relationship over the study period. The random effects panel regression models then have the advantage of capturing the dynamic influence of the weekly AI-generated public sentiment scores on the two financial performance variables, controlling for both time-varying and time-invariant firm characteristics. This allowed us to analyze how changes in these public sentiment scores impact financial performance (respectively, firm abnormal weekly returns and weekly price ranges).

Cross-sectional Analysis

Table 3 presents the first cross-sectional regression model results, where BHAR on firm-level ESG ratings, public sentiment on COVID-19-related signals, and other firm accounting controls. Column 1 only has the firm accounting control variables, while each sequential model includes either an ESG rating score (ESG composite, the Environment Pillar score, the Corporate Governance Pillar Score, or the Social Pillar Score) or a respective COVID-19-related public sentiment score. Industry dummies are included in all models, and standard errors are robust to heteroscedasticity. None of the ESG-related covariates are statistically significant, but all are positive except for SOCIAL. In contrast, for the public sentiment ratings, netSignals, economy, and socialImpact, are all positive and statistically significant. These coefficient estimates indicate that firms with positive public sentiment in economy (i.e., contributions towards the broader

economy), and social impact (i.e., quality of living, access to education, social distancing), on average, exhibited higher BHARs over the weeks from Jan. 8th, 2020, to Sept. 9th, 2020.

Table 3-3 Cross-sectional Regression Results, ESG Ratings and COVID-19-related Public Sentiment on Canadian Firm Buy-and-Hold Abnormal Returns

	Dependent variable:										
	log(1+BHAR)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ESG		12.433 (20.079)									
ENV			16.849 (15.823)								
GOV				16.583 (17.810)							
SOCIAL					(5.466) (13.021)						
net Signals						7.488*** (2.149)					
labour							(0.040) (4.662)				
supply Chain								1.043 (3.317)			
response									5.266 (4.711)		
economy										11.881*** (3.475)	
social Impact											13.264* (7.331)
TobinsQ	1.383 (3.470)	1.395 (3.511)	1.536 (3.562)	1.027 (3.546)	1.296 (3.475)	0.319 (3.388)	3.564 (3.907)	0.728 (3.520)	5.980 (4.898)	(1.077) (3.345)	1.920 (3.592)
size	(1.448) (1.327)	(2.201) (1.746)	(2.838) (1.756)	(2.196) (1.612)	(1.161) (1.428)	(1.085) (1.338)	-2.424* (1.441)	(1.159) (1.346)	(2.450) (1.662)	(1.895) (1.298)	(1.073) (1.356)
cash	4.068 (41.442)	1.150 (40.076)	(0.168) (40.162)	1.654 (40.773)	5.687 (40.566)	5.379 (40.294)	(21.840) (46.284)	8.141 (43.137)	(26.194) (51.858)	11.432 (40.925)	0.848 (41.614)
leverage	(10.238) (21.531)	(9.442) (21.738)	(7.575) (21.645)	(11.347) (21.797)	(10.911) (21.645)	(6.311) (20.794)	(17.000) (25.290)	(8.885) (23.027)	(17.158) (27.719)	(7.322) (21.020)	(11.420) (21.850)

ROE	17.553 (27.440)	19.192 (28.474)	20.682 (28.412)	18.882 (27.731)	16.575 (28.435)	14.796 (27.556)	26.292 (30.001)	16.150 (27.692)	36.004 (34.805)	14.683 (27.685)	16.479 (27.535)
dividend	-5.457*** (1.305)	-5.392*** (1.325)	-5.364*** (1.330)	-5.429*** (1.292)	-5.505*** (1.317)	-5.168*** (1.248)	-6.174*** (1.607)	-5.113*** (1.306)	-5.188*** (1.942)	-5.353*** (1.283)	-5.042*** (1.303)
historical Volatility	382.619* (229.537)	385.433* (229.592)	382.758* (224.843)	381.557* (225.525)	378.203 (233.776)	360.162 (230.746)	396.798 (242.721)	399.268* (230.635)	313.644 (248.092)	411.602* (242.632)	363.360 (227.707)
(Constant)	(0.304) (23.667)	0.161 (23.500)	3.895 (22.653)	0.212 (23.501)	0.528 (24.455)	8.914 (24.641)	5.070 (26.927)	(2.413) (25.080)	(2.181) (28.224)	(2.625) (24.817)	11.826 (24.252)
Observations	175.000	175.000	175.000	175.000	175.000	175.000	148.000	169.000	126.000	175.000	174.000
R ²	0.427	0.429	0.431	0.431	0.428	0.464	0.421	0.441	0.419	0.469	0.443
Adjusted R ²	0.365	0.363	0.366	0.366	0.362	0.402	0.340	0.373	0.321	0.408	0.378

Note: *p<0.1; **p<0.05; ***p<0.01
This table reports the cross-sectional regressions of abnormal buy-and-hold returns (transformed as the natural log of (1 + BHAR)), expressed as a percentage, from 2020-01-08 to 2020-09-09 on firm ESG ratings or firm-level COVID-19-related public sentiment signals. All accounting variables are Winsorized at the 1% level in each tail. All specifications include industry dummies, but are removed from the table for brevity. Standard errors are robust to heteroscedasticity and are included in parentheses under each coefficient estimate. Table A1 in the appendix defines all variables used in this paper

Next, table 4 presents the results of another cross-sectional analysis. The dependent variable is the median of weekly price ranges per firm, where the weekly price range is scaled by the midpoint. Column 1 in Table 4 again only includes the accounting control variables, with each sequential model specification including an ESG rating or public sentiment COVID-19-related score. Only one of the ESG rating-related covariate estimates is statistically significant; GOV, or the Corporate Governance pillar is positive and statistically significant, but only at the 0.1 level. Like Table 3, the public sentiment ratings covariate estimates show a stronger ability to explain financial performance. The following are negative estimates and statistically significant, netSignals, labour and economy. This indicates that firms that had higher positive sentiment concerning their labour force or their contribution to the broader economy were regarded as having lower stock price volatility, possibly suggesting a potential mitigating effect from market instability.

Table 3-4 Cross-sectional Regression Results, ESG Ratings and COVID-19-related Public Sentiment on Canadian Firm Median Weekly Price Ranges

	Dependent variable:										
	Median Scaled Range Percentage										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ESG		0.662 (0.450)									
ENV			0.544 (0.430)								
GOV				.656* (0.371)							
SOCIAL					0.372 (0.356)						
netSignals						-0.155*** (0.055)					
labour							-0.200** (0.099)				
supply Chain								0.054 (0.081)			
response									(0.057) (0.105)		
economy										-0.298*** (0.107)	
social Impact											(0.054) (0.200)

TobinsQ	-.237** (0.111)	-.236** (0.114)	-.232** (0.111)	-.251** (0.115)	-.231** (0.112)	-.214** (0.108)	-.288** (0.120)	-.236** (0.113)	-.311* (0.165)	-.175* (0.102)	-.239** (0.113)
size	-.152*** (0.044)	-.192*** (0.058)	-.197*** (0.063)	-.182*** (0.049)	-.172*** (0.051)	-.160*** (0.044)	-.111*** (0.042)	-.157*** (0.045)	-.119** (0.050)	-.141*** (0.040)	-.157*** (0.045)
cash	1.113 (1.043)	0.957 (1.025)	0.976 (1.007)	1.017 (1.045)	1.002 (1.032)	1.085 (1.013)	1.691 (1.114)	0.987 (1.081)	1.691 (1.434)	0.928 (0.950)	1.075 (1.062)
leverage	(0.537) (0.708)	(0.495) (0.705)	(0.452) (0.709)	(0.581) (0.702)	(0.492) (0.714)	(0.619) (0.688)	(0.758) (0.697)	(0.606) (0.757)	(0.809) (0.928)	(0.611) (0.668)	(0.531) (0.708)
ROE	(0.703) (0.490)	(0.616) (0.477)	(0.602) (0.468)	(0.651) (0.479)	(0.637) (0.487)	(0.646) (0.469)	-.863* (0.507)	(0.691) (0.496)	(0.719) (0.647)	(0.631) (0.435)	(0.686) (0.492)
dividend	(0.024) (0.039)	(0.021) (0.037)	(0.021) (0.037)	(0.023) (0.038)	(0.021) (0.038)	(0.030) (0.039)	(0.018) (0.044)	(0.025) (0.040)	(0.063) (0.062)	(0.027) (0.038)	(0.029) (0.040)
historical Volatility	30.330*** (8.427)	30.480*** (8.303)	30.335*** (8.248)	30.288*** (8.302)	30.631*** (8.390)	30.797*** (8.073)	28.762*** (8.680)	30.190*** (8.479)	26.861*** (9.792)	29.604*** (7.772)	30.292*** (8.366)
(Constant)	3.334*** (0.773)	3.359*** (0.776)	3.470*** (0.811)	3.355*** (0.761)	3.278*** (0.765)	3.143*** (0.727)	2.982*** (0.836)	3.454*** (0.791)	3.491*** (0.951)	3.392*** (0.699)	3.321*** (0.775)
Observation s	175.000	175.000	175.000	175.000	175.000	175.000	148.000	169.000	126.000	175.000	174.000
R ²	0.736	0.739	0.739	0.741	0.738	0.748	0.738	0.733	0.701	0.756	0.738
Adjusted R ²	0.708	0.709	0.709	0.711	0.707	0.719	0.702	0.700	0.650	0.728	0.708

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the cross-sectional regressions of median of weekly price ranges, scaled by the midpoint of the range from 2020-01-08 to 2020-09-09 on firm ESG ratings or firm-level COVID-19-related public sentiment signals. All accounting variables are Winsorized at the 1% level in each tail. All specifications include industry dummies, but for brevity are omitted from the table. Standard errors are robust to heteroscedasticity and are included in parentheses under each coefficient estimate.

Table A1 in the appendix defines all variables used in this paper

Random Effect Panel Analysis

For the first random effect analysis on weekly AR, Table 5 presents the results of model specifications with a respective AI-generated public sentiment score, accounting controls and industry dummies. The netSignals, labour, and supplyChain signals are all positive and statistically significant, indicating a positive relationship with weekly abnormal returns. The other covariates of interest, response, economy, and socialImpact, are not statistically significant but the coefficient estimates are all positive. Overall, these results suggest that the stock market reacted favourably towards positive sentiment regarding labour and supply chain issues but also did not react negatively towards higher positive sentiment on response, economy and social impact, respectively. Related to the reasons for running both cross-sectional and panel analyses, it is important to bring attention to the inconsistent number of observations in these models. In the public sentiment dataset, if a firm did not have any mentions in the data sources for that week, no sentiment rating was generated. Among the five sub-signals, the lowest number of observations over the full time span of the study are response with 778 and labour with 1,229, which possibly explains the negative adjusted R² value. The number of observations in the other columns is as such: supply chain (n = 1,465), economy (n = 2,981), socialImpact (n = 2,520), and the aggregate of netSignals (n = 3,233).

Table 3-5 Random Effects Panel Regression Results, ESG Ratings and COVID-19-related Public Sentiment on Canadian Firm Weekly Abnormal Returns

	Dependent variable:					
	WeeklyAbnormalReturn					
	(1)	(2)	(3)	(4)	(5)	(6)
netSignals	.155*** (.060)					
labour		.488* (.263)				
supplyChain			.769*** (.277)			
response				.523 (.352)		
economy					.124 (.089)	
socialImpact						.287 (.200)
(Constant)	2.143* (1.122)	1.750 (2.748)	4.786** (2.046)	.091 (4.996)	2.017* (1.106)	3.038** (1.192)
Observations	3,242	1,234	1,466	780	2,990	2,529
R ²	.020	.014	.025	.012	.019	.018
Adjusted R ²	.014	-.001	.012	-.011	.013	.011
F Statistic	64.282***	17.082	36.404***	9.212	56.238***	45.585***

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the results of the random effect estimations of abnormal weekly returns from 2020-01-01 to 2020-09-09 on firm-level COVID-19-related public sentiment signals. All accounting variables are Winsorized at the 1% level in each tail. All specifications include industry dummies. Both the control accounting variables and industry dummies are omitted from the table for brevity. Standard errors are clustered by firm to allow for heteroscedasticity and serial correlation and are included in parentheses under each coefficient estimate.

Table A1 in the appendix defines all variables used in this paper.

Our final model employs a random effect panel analysis, where we focussed on weekly price range as the dependent variable. Findings in Table 6 indicate statistical significance for netSignals, supplyChain, and economy. All indicate that higher public sentiments on these COVID-19-related issues are associated with decreased stock price volatility. The other public sentiment coefficient estimates are not statistically significant; however, labour and response are both negative. Again, given the relatively smaller number of observations, it is unclear whether these estimates are representative. If we assume that they are for publicly traded Canadian firms, these models do suggest that the stock market had a neutral reaction to sentiment regarding labour and response issues. The latter is for firms that invested in R&D or efforts towards crisis-specific goods. Further, the only coefficient for the variables of interest that is positive is socialImpact, but it is not statistically significant. This does suggest that the stock market did not react negatively toward sentiment concerning the social impact-related responses of firms.

Table 3-6 Random Effects Panel Regression Results, ESG Ratings and COVID-19-related Public Sentiment on Canadian Firm Weekly Price Range

	Dependent variable:					
	WeeklyPriceRange					
	(1)	(2)	(3)	(4)	(5)	(6)
netSignals	-.376*** (.061)					
labour		-.303 (.215)				
supplyChain			-.750*** (.189)			
response				-.173 (.385)		
economy					-.713*** (.089)	
socialImpact						.078 (.151)
(Constant)	6.752*** (2.365)	7.362* (4.175)	6.575* (3.499)	8.544* (4.979)	7.557*** (2.366)	8.315*** (2.627)
Observations	3,242	1,234	1,466	780	2,990	2,529
R ²	.100	.142	.127	.119	.109	.092
Adjusted R ²	.095	.130	.116	.098	.104	.085
F Statistic	256.344***	101.485***	102.502***	50.162***	262.201***	135.603***

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the results of the random effect estimations of weekly price range from 2020-01-01 to 2020-09-09 on firm-level COVID-19-related public sentiment signals. All accounting variables are Winsorized at the 1% level in each tail. All specifications include industry dummies. Both the control accounting variables and industry dummies are omitted from the table for brevity. Standard errors are clustered by firm to allow for heteroscedasticity and serial correlation and are included in parentheses under each coefficient estimate.

Table A1 in the appendix defines all variables used in this paper.

3.5 Discussion

This research enhances the understanding of the complex relationship between ESG performance and financial performance during the COVID-19 pandemic, highlighting the efficacy of AI-generated public sentiment data as a useful component of the overall investor toolkit in times of crisis. Given recent advancements in AI as well as debates and scrutiny surrounding ESG data quality by academic, government, and private sector actors (Edmans, 2023; Pérez et al., 2022), this research is timely and contributes to the growing debate about measuring ESG performance. Our findings address Hughes et al. (2021) assertions about whether AI-generated public sentiment data could be used as part of a broader set of tools and methods for monitoring and managing ESG issues during crises.

In revisiting our research question, we asked, how does AI-generated public sentiment data compare with conventional ESG performance data in offering material insights about the financial performance of Canadian firms during the COVID-19 pandemic? Our findings indicate that AI-generated public sentiment data correlates more strongly with financial returns and stock price volatility during this crisis than conventional ESG data. This suggests that AI-generated data not only capture a broader range of variables that affect financial performance but also reflect materiality more effectively than conventional ESG data. These results have significant implications for investors seeking to enhance their decision-making processes during crises, supporting the notion that stakeholders can embrace innovation to achieve a more nuanced understanding of dynamic materiality using timely insights (Kuh et al., 2020). In shedding light on these dynamics, our study uncovered several noteworthy dimensions related to financial returns and stock price volatility.

First, firms with positive sentiment regarding the economy, reflecting the broader, global economic situation and outlook, experienced enhanced returns and reduced stock price volatility. This aligns with Carroll's (2016, p. 3) perspective that economic responsibility is a “fundamental condition or requirement of existence” that is “required by society”. Without a strong economic foundation, firms cannot sustain environmental and social practices, nor will ESG performance be rewarded in the absence of financial performance. Positive news about the economy ignites investor confidence, leading to favourable outcomes for firms, supporting Waddock & Graves’ (1997) notion that good management strategies reflect enhanced stakeholder satisfaction and financial performance. Strategy scholars like Vanacker et al. (2017) have noted the key role of managers in orchestrating activities such as resource allocation and deployment in shaping financial performance, further signifying that a firm's capacity to respond to economic signals indicates the overall quality of its management.

Second, positive sentiment about supply chain also enhanced returns and reduced stock price volatility. Firms that managed their supply chains effectively during the pandemic maintained investor confidence and stability in their financial performance. This aligns with research (Chen et al., 2023; Cheng et al., 2022) showing that disruptions, such as lockdowns and physical distancing, in the global supply chain significantly impact investor behaviour.

Finally, positive sentiment regarding social impact enhanced returns. According to Truvalue Labs, social impact was the most discussed topic among the five sub-signals during the first quarter of 2020 (FactSet, 2021). As the world shifted its focus to contributing to or improving societal outcomes, investors held firms accountable during a time when the social contract between managers and their stakeholders shifted (PRI, 2020). This supports our notions about

dynamic materiality and the relationship between a firm's stakeholder satisfaction efforts and its financial performance. We also believe that a significant contributor to social impact was the ensuing COVID-19 vaccine announcements, which prompted positive investor attitudes and influenced the market rally. Numerous studies corroborate our interpretation, showing that stocks reacted positively to vaccine news (Kucher et al., 2023; Martins & Cró, 2022).

Our study offers theoretical contributions in several ways by building on Waddock and Graves' (1997) notions of good management theory through the lens of crisis. First, AI-generated public sentiment data, comprising of COVID-specific sub-signals provide a more nuanced understanding of dynamic materiality, demonstrating the relationship between a firm's stakeholder satisfaction efforts and its financial performance. This data allows for more timely insights into changing stakeholder perceptions and market behaviour. In contrast, conventional ESG data, which are suited for assessing static materiality, serve as a more general proxy for stakeholder satisfaction. While prior works (e.g., Waddock & Graves, 1997) have used conventional ESG data to explain good management theory, our findings demonstrate that AI-generated public sentiment data, sourced weekly, is a more effective indicator for stakeholder satisfaction. This reshapes the understanding of good management theory and expands its applicability to include the nuances of dynamism during the pandemic era. Second, our study highlights the multi-faceted nature of stakeholder satisfaction in crisis periods, encompassing a combination of financially and non-financially related sub-signals that distinctively influence returns and risk reduction. The use of AI-generated public sentiment data as a weekly indicator of stakeholder satisfaction hence enables a deeper understanding of this interplay during the pandemic as well as into dynamic materiality as it relates to good management theory. The

contrast of strategies and implications shown in our study necessitates firms to adopt flexible governance structures and embrace good management practices that can quickly respond to changing scenarios. This points to the need for agility and strategic financial management as critical components for navigating through crises, thus aligning with Van Essen et al. (2013) and Flammer and Ioannou (Flammer & Ioannou, 2021) assertions on the significance of economic responsibility, decisive management, and investments in stakeholder satisfaction for firm resilience and competitiveness.

Novel methodological contributions were also made in this paper as evidenced by the data and results to examine how AI-generated public sentiment ratings compare to conventional ESG data in offering material insights. While prior works (e.g., Christensen & Serafeim, 2019; Svanberg et al., 2022) have used AI approaches to examine ESG, our study is the first of its kind to provide a comparative analysis between conventional ESG data and AI-generated public sentiment data, and how they correspond to financial performance data of firms in times of crisis. The results showed that during crises, AI-generated public sentiment ratings can serve as a stronger proxy for stakeholder satisfaction by offering more timely pandemic insights, which enable a deeper understanding of dynamic materiality.

Importantly, we acknowledge limitations observed in our random effect panel analysis related to the varying sample sizes of the sub-signals (i.e., labour and response). To address these challenges, we encourage future research to investigate the relationship between public sentiment and financial performance during different phases of the pandemic. We also encourage scholars to extend our research inquiry to firms situated in diverse geographical territories and economic systems; to assess the universality and robustness of the findings we observed in the Canadian

context. As our study employs ESG data from 2019, future research can source 2020 (and beyond) data to help determine whether ESG vendors adjusted or revised their data or methodology in the wake of a pandemic.

Finally, we address a gap in the study of ESG research as it relates to the financial performance of Canadian firms during the COVID-19 pandemic. While extant literature has examined this relationship since the advent of the crisis, to our knowledge, this study is the first of its kind to investigate and offer AI-generated insights exclusively about Canadian firms.

3.6 Conclusion

Over four years have passed since COVID-19 first caused calamity in virtually every aspect of human life. The resulting macroeconomic crisis presented significant challenges, deeply impacting global systems. However, it has also provided an opportunity to evaluate the resilience of our environmental and societal health, including our ability to create value and maintain corporate commitments to sustainability in times of crisis.

Despite the dramatic interest and investment in ESG practices leading up to the pandemic, and the presumption that ESG performance offered resiliency to firms during this crisis, debate and controversy surrounding the legitimacy of ESG ratings and data have never been greater. Investors must carefully navigate how to manage and integrate ESG into their investment process while minimizing the potential costs imposed on portfolio construction by ESG constraints (Henriksson et al., 2019).

This unexpected crisis allowed us to compare AI-generated public sentiment data with conventional ESG ratings in offering insights during the market crash in the first quarter of 2020

and the rally that followed. Our research explored these dynamics within the context of Canadian firms.

In response to this growing debate, the extensive analyses carried out in this study offer several findings. First, AI-generated public sentiment ratings served as a stronger proxy for stakeholder satisfaction by offering more timely pandemic insights, which enabled a more nuanced understanding of dynamic materiality. Specifically, our findings showed that AI-generated public sentiment data correlated more strongly with financial returns and market volatility during this crisis than conventional ESG data. Such data not only captures a broader range of variables that affect financial performance but also reflects materiality more effectively than conventional ESG data.

Moreover, our findings showed that firms with positive economic and supply chain sentiment experienced enhanced returns and reduced stock price volatility, while those with positive sentiment around social impact also saw reduced stock price volatility. This suggests that investor confidence and effective management strategies lead to favourable financial outcomes.

Finally, this exploratory study offers theoretical and methodological contributions to the literature. While prior works (e.g., Waddock & Graves, 1997) have used conventional ESG data for explaining good management theory, our findings show that weekly sourced AI-generated public sentiment data is a more effective indicator for stakeholder satisfaction, thus reshaping the understanding of good management theory and expanding its applicability to include the nuances of the pandemic era.

The findings of this study address limitations noted by prior works and have practical implications for stakeholders, investors, and managers navigating the intricate landscape of sustainable finance considerations during crises. These results are significant for investors seeking to enhance their decision-making processes during crises.

The analysis in Chapter 3 demonstrated the comparative strengths and limitations of ESG ratings and AI-generated sentiment as proxies for stakeholder satisfaction during the COVID-19 crisis, highlighting how time-sensitive measures can reshape our understanding of firm resilience. Chapter 4 extends this inquiry by integrating the firm-level lens of ESG performance with the macroeconomic dimension of fiscal stimulus, testing how these factors interact to influence corporate financial stability. In doing so, it moves beyond firm-specific measures to assess how government interventions altered the landscape of resilience across the broader financial system.

MANUSCRIPT ENDS

4. ECONOMIC STIMULUS OR ESG: WHAT HELPED ‘IMMUNIZE’ FIRMS FROM COVID-INDUCED MARKET VOLATILITY?

The fourth chapter (February 2024 – November 2024) explores financial and non-financial factors that contributed to firm resilience during this period. Specifically, we evaluate the impact of economic stimulus and ESG performance on financial performance during market volatility. Our research analyzes two predominant perspectives: the first attributes firm resilience to economic stimulus measures like the Canadian COVID-19 Economic Response Plan, which stabilized markets by reducing volatility and enhancing returns. The second perspective suggests that firms with strong ESG performance experienced enhanced returns and reduced risk. Given that economic stimulus operates at the macro level while ESG performance is a firm-level factor, this study adopts a multilevel approach. This framing allows for a more nuanced analysis of their distinct and interacting roles.

By incorporating slack resource theory, we demonstrate that economic stimulus serves as a moderating factor by creating fiscal space and slack resources, providing firms with resilience during the pandemic. Due to the rapidly evolving nature of the pandemic, and in turn, investor behaviour, the adaptation of slack resource theory acknowledges the concept of dynamic materiality by utilizing weekly sourced AI-generated public sentiment data. Moreover, this framework provides a unique opportunity to assess whether sub-signals derived from AI-generated public sentiment data can explain the impact of economic stimulus on variables such as market volatility and financial returns.

MANUSCRIPT BEGINS

4.1 Introduction

In quarter one (Q1) of 2020, the coronavirus disease 2019 (COVID-19) pandemic spurred fears among investors, which translated into significant market drops (Folger-Laronde et al., 2020). In the following months, however, markets experienced a notable rally as investor sentiment gradually stabilized, driven by optimism around potential recovery and adaptation to the new economic landscape (Pashang et al., submitted). The discourse surrounding the resilience of firms during market volatility pivots on three schools of thought.

The first argues that fiscal, monetary, and macroprudential policies (henceforth referred to as economic stimulus) played a pivotal role in stabilizing volatile markets and enabling firms to recover (Nerlich & Reuter, 2015), as demonstrated by Hsu and Liao's (2022) findings on the US's intervention reducing volatility and improving stock returns. Proponents of the second perspective argue that superior environmental, social, and governance (ESG) performance leads to risk reduction and higher returns (Albuquerque et al., 2020; Broadstock et al., 2021). The pandemic led to a large collection of empirical studies on ESG performance, initially showing a positive relationship with financial performance during the market crash, though later research presented mixed or inconclusive results (Pashang et al., submitted). The third school of thought suggests that investors favoured traditional accounting and market-based measures such as leverage, liquidity, and investment in intangible assets (Demers et al., 2021).

While all three perspectives provide valuable insights, this paper primarily examines the comparative and interacting effects of economic stimulus and ESG performance on firm resilience during the COVID-19 crisis. In the field of sustainable finance, the role of economic stimulus in stabilizing markets and supporting firms during crises remains underexplored. This

gap offers a unique opportunity for further research, particularly in understanding how such policies intersect with corporate sustainability strategies, and how government interventions affect firm performance. A critical question remains: how does economic stimulus compare and interact with ESG performance in stabilizing financial performance during COVID-induced market volatility? Given that economic stimulus operates at an economy-wide level, while ESG performance is a firm-level factor, this study takes a multilevel approach to analyze their distinct and intersecting roles in stabilizing financial performance during market volatility.

We draw on slack resource theory and good management theory, developing a theoretical framework that applies a crisis lens to Waddock and Graves' (1997) conceptualizations that suggest firms with slack resources and good management have greater freedom to invest in ESG activities, enhancing financial performance and corporate social performance⁷. Together, this results in a virtuous cycle of improved performance (Waddock & Graves, 1997). Thus, ESG performance becomes both a predictor and a consequence of financial performance, indicating a contemporaneous and bidirectional relationship (Orlitzky et al., 2003; Waddock & Graves, 1997). The dynamics of slack resource theory and good management theory during crisis periods can differ drastically from those observed during non-crisis conditions, which have been the focus of most prior research (Coelho et al., 2023). During crises, slack resources may not only provide firms with a buffer to absorb shocks but also afford them the flexibility to leverage opportunities, aligning with good management theory's notion that good management, demonstrated through the strategic use of available resources, plays a pivotal role in navigating through uncertainty.

⁷ Henceforth, we express Waddock and Graves (1997) notions of corporate social performance as ESG performance.

We employed pooled regression analysis, incorporating control variables and interaction terms to analyse the relationship between economic stimulus, ESG performance, and financial performance. Two sets of regressions were conducted: pooled regression models for each year and interaction models to explore the moderating effects of economic stimulus. We used abnormal returns and weekly price range as dependent variables, with ESG performance and control variables as the independent variables.

The findings of this study offer several contributions to both academic and industry stakeholders. First, our study is the first of its kind to investigate the comparative and interacting impacts of economic stimulus and ESG performance on Canadian firms during the pandemic.

Second, our contribution advances slack resource theory by integrating the concept of fiscal space, which represents a government's capacity and flexibility to use economic stimulus as a protective measure against crises-induced volatility. This integration helps firms manage crisis-induced market volatility through the creation of slack resources, with economic stimulus acting as a moderating factor. This extension broadens the applicability of slack resource theory while complementing good management theory by demonstrating how effective management utilizes slack resources to maintain stability. In non-crisis settings, good management theory emphasizes that good management practices such as sustainability activities enhance ESG and financial performance. However, prior research (e.g., Pashang et al., submitted) indicates that effective managers may need to prioritize immediate financial resilience over traditional ESG commitments when addressing investor expectations.

The remainder of this chapter is structured as follows. Section 2 provides a literature review and the hypotheses that drive the empirical analyses of the study. Section 3 outlines the

research methodology, including data sources and analytical techniques. Section 4 presents the statistical analyses and discusses the findings. Finally, Section 5 offers conclusions, limitations, and future research directions.

4.2 Literature review and hypothesis development

Fiscal Space and Economic stimulus as ‘immunization’

The COVID-19 pandemic had a more severe impact on financial markets than previous health crises, largely due to the scale and magnitude of the global economic shutdown (Liu et al., 2022). Investor fear contributed to heightened market volatility worldwide (Li et al., 2021). In response, G20 nations delivered unprecedented fiscal support within the first month of the pandemic, surpassing the fiscal stimulus provided in the three years following the 2008 GFC (Government of Canada, n.d.). This intervention pushed global government debt to 99% of GDP in 2020 (Kose et al., 2021). Canada, due to its strong pre-crisis fiscal space and countercyclical capacity, implemented extensive support to ensure businesses had access to credit (Government of Canada, n.d.).

Fiscal space, defined as the pre-existing budgetary capacity allowing fiscal policy for economic stimulus or financial recapitalization (Romer & Romer, 2019), played a crucial role in shaping stimulus strategies (Nerlich & Reuter, 2015). In this paper, fiscal space represents a government’s capacity and flexibility to use economic stimulus as a protective measure against crises-induced volatility. Countries that had implemented macroprudential tightening before the pandemic were better positioned to weather its economic and financial stresses (Bergant & Forbes, 2023). These nations could ease these policies more aggressively when the crisis hit, highlighting the importance of creating fiscal space during growth periods. Bergant & Forbes

(2023) further found that fiscal space played a larger role than country-specific factors in determining responses to economic, financial, and health-related shocks. Nerlich & Reuter (2015) found that greater fiscal space is linked to increased discretionary expenditures or reduced revenues. For instance, Canada, with the lowest net debt-to-GDP ratio among G7 and G20 nations, was able to deliver one of the most agile and significant fiscal responses (Government of Canada, n.d.). The Canadian government introduced comprehensive measures equivalent to 19.7% of GDP (\$435.2 billion) (IMF, n.d.).

Evidence from the pandemic suggests that such policies played an important role in stabilizing markets. Hsu & Liao (2022) for instance found that the US's Coronavirus Aid, Relief, and Economic Security (CARES) Act significantly reduced market volatility and improved stock returns. In Canada, the COVID-19 Economic Response Plan was deployed indiscriminately, promoting a level playing field among firms (Government of Canada, n.d.). According to OECD (2024), the principle of competitive neutrality was critical during the crisis, as it enabled both high-performing and struggling firms to access essential liquidity, effectively stabilizing the competitive landscape. These interventions, though seen as essential in mitigating a deeper economic crisis, have revealed complex implications for firms with strong ESG performance (Albuquerque et al., 2020).

ESG Performance as 'Immunization'

The relationship between ESG performance and financial performance remains a subject of debate, with some studies suggesting a positive relationship (Verheyden et al., 2016). For instance, in the second-order meta-analysis by (Friede et al., 2015), they found that among 25

unique meta-analyses that span from 1997 to 2015, a distinct positive relationship between ESG and financial performance persists in the empirical work.

In times of crisis, it is the main function of ESG metrics to capture firm performance, as accurately as possible, so that investors can evaluate companies and that firms can understand how to respond and adapt to unfolding events (Kotsantonis & Serafeim, 2019). Pashang et al. (submitted) noted that early research on the pandemic indicated a positive relationship between ESG performance and financial performance during the market crash. However, subsequent studies revealed a mixed or inconclusive relationship as the crisis evolved (Pashang et al., submitted). Prior research that has examined financial factors (i.e., accounting-based variables) identifies these as critical indicators of organizational behaviour, performance, and resilience during crises (Demers et al., 2021; Ramelli et al., 2020). These studies suggest that financial metrics, rather than ESG performance, offer more reliable insights into firms' ability to withstand and recover from economic shocks. In parallel, this paper argues that economic stimulus also plays a crucial role in firm resilience, highlighting the importance of financial rather than non-financial factors in providing resilience during crises.

Government intervention during the pandemic blurred the competitive advantages that firms with strong ESG performance typically hold, as fiscal measures provided liquidity universally, irrespective of firms' commitment to sustainable practices (Duque-Grisales & Aguilera-Caracuel, 2021). Consequently, this intervention weakened the direct relationship between ESG strength and financial resilience, diminishing the distinction between high and low ESG performers during the crisis (Duque-Grisales & Aguilera-Caracuel, 2021). Similar conclusions were drawn by Albuquerque et al. (2020), who found that fiscal stimulus measures

acted as an institutional equalizer, reducing the inherent competitive advantage traditionally associated with high-ESG firms.

Despite this levelling effect, ESG-focused firms demonstrated a degree of resilience. An analysis by de Renzis and Mosson (2024) revealed that ESG funds exhibited superior performance and experienced higher net inflows compared to non-ESG funds during the pandemic. However, the broad liquidity support provided to all firms mitigated what could have been a more pronounced divergence in performance between ESG and non-ESG entities. This underlines the complex role of economic stimulus, which, while essential in averting further volatility, also resulted in diminished differentiation based on ESG performance. The ongoing academic discourse about whether ESG performance provides resilience for firms during crises highlights the complex nature of this sub-field in sustainable finance (Folger-Laronde et al., 2020).

Theoretical Framework: Slack Resource Theory and Good Management Theory During a Global Crisis

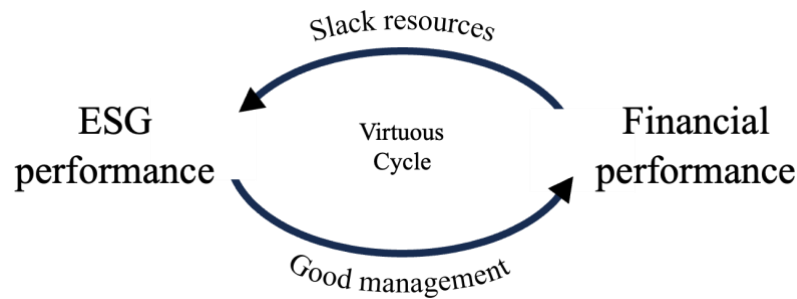
In the context of sustainable finance, Waddock and Graves (1997) argued that the availability of slack resources is positively associated with a firm's ESG performance, while good management practices further enhance financial performance.

Drawing from a resource-based view (e.g., Penrose, 1959) and behavioural theory of the firm (e.g., Cyert & March, 1963), slack resource theory suggests that slack resources, defined as the level of availability of a resource that can be deployed flexibly, enable firms to improve financial performance, undertake new ESG initiatives, or optimize processes (Bradley et al.,

2011; Daniel et al., 2004). Daniel et al. (2004) conducted a seminal meta-analysis corroborating a positive correlation between all three types of slack (i.e., available, recoverable, and potential) and financial performance. In non-crisis periods, slack resource theory suggests that strong financial performance generates slack resources, giving firms the flexibility to invest in ESG initiatives – a reflection of the notion of ‘doing good by doing well’ (Waddock & Graves, 1997).

Good management theory, a nuanced interpretation of stakeholder theory, asserts that firms with effective management practices like stakeholder management, innovation, and community relations achieve better ESG performance, driving financial success (Waddock & Graves, 1997). Research supports a bidirectional relationship between ESG and financial performance: strong financial outcomes enhance ESG performance, and vice versa (McGuire et al., 1988, 1990; Orlitzky et al., 2003; Waddock & Graves, 1997). Financial success often provides advantages such as enhanced reputation, stronger investor relations, better access to capital and the ability to attract top talent (Orlitzky et al., 2003). This virtuous cycle is documented: Waddock and Graves (1997) found that financial performance boosts ESG outcomes (aligning with slack resource theory), while strong ESG performance drives financial performance (consistent with good management theory). This suggests that ESG performance both determines and results from improved firm performance, highlighting the reciprocal interaction between slack resources, ESG activities, and firm performance. As illustrated in Figure 1, these findings highlight the dynamic and the bidirectional relationship between these dimensions over time (Waddock & Graves, 1997).

Figure 4-1 Slack Resource Theory and Good Management Theory During Non-crisis Periods



Note: This figure illustrates the application of slack resource theory and good management theory during non-crisis periods, where strong financial performance enables firms to accumulate slack resources. Source: Adapted from Waddock and Graves (1997).

The application of slack resource theory and good management theory in periods of market volatility, particularly in the context of the COVID-19 pandemic, remains underexplored. To address this gap, we adopt a multilevel approach, recognizing that economic stimulus functions at the macroeconomic level, whereas ESG performance is inherently firm-specific, influencing firm-level strategies. Previous research, such as Bradley et al. (2011), has demonstrated a positive relationship between slack and financial performance, particularly for firms operating in both hostile and stable environments. Jin et al. (2022) further indicated that slack resources can absorb external volatility and mitigate the impacts of a recession. Nevertheless, most studies have not comprehensively addressed the comparative and interacting roles of economic stimulus and ESG performance in periods of crisis. For instance, Li (2021) found a positive moderating effect of organizational slack on the pandemic–firm performance relationship. However, generalizations were limited to the manufacturing sector. Similarly, Cardillo et al. (2023) and Jin

et al. (2022) found positive relationships between slack and financial performance during the pandemic, focusing on European and Chinese markets, respectively.

During the COVID-19 pandemic, economic stimulus measures implemented by G7 countries played a key role in maintaining competitive neutrality, a principle emphasized by the OECD (2024). It was argued that widespread adoption of Keynesian-style stimulus prevented significant market fallout, maintaining competition among firms irrespective of their pre-pandemic financial performance (Makin & Layton, 2021; OECD, 2024). From a slack resource theory perspective, the economic stimulus can be seen as an extension of a firm's slack resources, irrespective of the firm's performance or ESG initiatives. This intervention enabled financially weaker firms, which might have otherwise struggled, to endure alongside high-ESG firms, thus levelling the competitive playing field (Nerlich & Reuter, 2015). The equalizing effect of fiscal intervention acted as a moderator, weakening the relationship between ESG performance and financial outcomes.

Existing literature has examined the dynamics between ESG performance and financial performance, as well as the effects of economic stimulus on financial performance, in isolation. However, limited attention has been given to a comparative and interacting analysis of ESG performance and economic stimulus as variables during COVID-induced market volatility. To bridge this gap, we developed a theoretical framework that situates Waddock and Graves' (1997) conceptualizations of slack resource theory and good management theory within the context of a crisis.

Our theoretical framework, as illustrated in Figure 2, suggests that fiscal space enables economic stimulus to function as an 'immunizing' mechanism against market volatility. Viewed

through the lens of slack resource theory, this fiscal capacity allows firms to maintain resilience, thereby fulfilling stakeholder expectations, even under challenging economic conditions. Moreover, we argue that strong ESG performance positively relates to enhanced financial performance. Yet, the institutional effect of the economic stimulus acted as a moderator, weakening the distinct advantage of ESG-focused firms and effectively levelling the playing field between ESG and non-ESG firms.

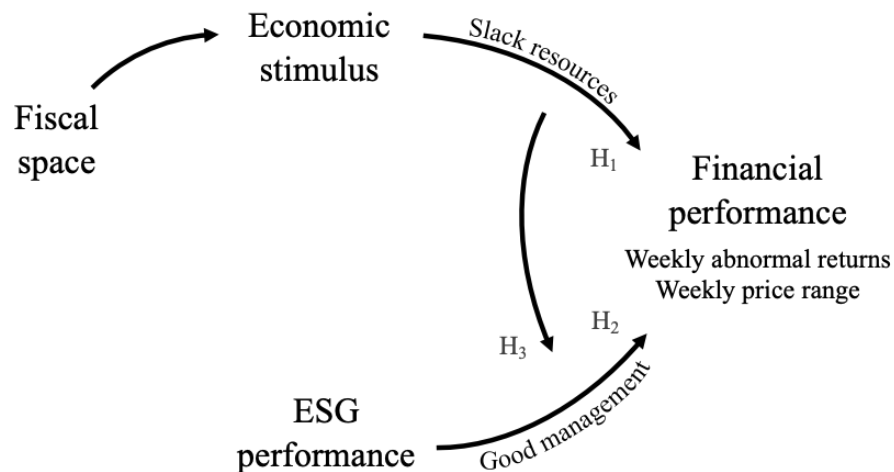
We hypothesize the following:

Hypothesis 1: Economic stimulus significantly contributed to improving financial performance during the COVID-19 pandemic.

Hypothesis 2: ESG performance significantly contributed to improving financial performance during the COVID-19 pandemic.

Hypothesis 3: Economic stimulus weakens the relationship between ESG performance and financial performance

Figure 4-2 Impact of economic stimulus and ESG performance on financial performance during the COVID-19 pandemic



Note: This figure illustrates the theoretical model demonstrating how fiscal space, economic stimulus, ESG performance and financial performance interact. Source: Authors.

4.3 Data and Methodology

Sample and Summary Statistics

This study utilized a combination of non-financial and financial data for Canadian firms to examine the impact of economic stimulus and ESG performance on weekly financial performance before (2019), during (2020), and after (2023) the COVID-19 pandemic. Most of the empirical work on ESG, firm performance, and crisis behaviour has centred on U.S. companies or aggregated G20 samples (Cheema-Fox et al., 2020; Albuquerque et al., 2020). Canadian firms have been largely overlooked, despite Canada's unique institutional and policy environment during the COVID-19 crisis. This represents a clear research gap that this study addresses directly. The non-financial data sources include ESG ratings from Refinitiv. The financial data, including market and accounting variables, were sourced from Compustat. To determine the sample per year, the ESG performance dataset and accounting and market data were combined. Firms only with complete data across each respective year were kept in the sample. Further, firms from the financial and real estate industries were removed from the sample to mitigate potential biases stemming from sector-specific financial characteristics (Demers et al., 2021). These sectors operate under specialised models that differ substantially from the rest of the economy: they are capital-intensive, tightly regulated, and interconnected with systemic financial structures. Their performance and risk exposures are shaped as much by regulation and macro-financial dynamics as by firm-specific strategy. The number of firms per year is not equal due to data availability across the datasets, mergers and acquisitions, and firms

that did not survive the COVID-19 pandemic. The number of firms per year is as follows: 2019 (148 firms with 52 observations each), 2020 (176 firms with 36 observations each), and 2023 (165 firms with 52 observations each). The reduced number of weeks in 2020 (36 instead of 52) reflects our focus on examining the moderating role of economic stimulus, rather than covering the full 52-week period. The chosen window therefore provides an intensive test of market resilience and volatility during the pandemic's most turbulent phase.

Refinitiv ESG data. The ESG data utilized in this study was sourced from Thomson Reuters Refinitiv, which offers comprehensive ratings across environmental, social, and governance (ESG) dimensions. These ratings are based on over 600 metrics derived from publicly available data and are used in prior works to measure ESG performance (Albuquerque et al., 2020; Demers et al., 2021). Refinitiv provides an aggregate ESG score per firm per year. The ESG ratings were measured in the year before the respective financial performance dependent variables (e.g., for the 2020 model specifications, Refinitiv ESG ratings from 2019 are used to measure ESG performance). To allow for cleaner interpretations and to identify top ESG performers, ESG was measured as a dummy variable where firms in the top quartile were given a 1 and 0 otherwise. The ESG ratings per firm may change over the years, so this dummy variable was constructed per year.

Corporate financial performance variables. The study employed two dependent variables: weekly abnormal returns and weekly price range. To minimise the potential bias of end-of-week market activity, these two variables are based on Wednesday to the following Tuesday. Weekly

abnormal returns were calculated as the difference between the weekly logarithm returns (sum of daily returns for the week) of a stock and the CAPM beta multiplied by the weekly logarithm return of the TSX. The CAPM beta was estimated using weekly returns from the prior year. Although multifactor approaches such as Fama–French have become standard in long-horizon studies of asset pricing, their application during crisis periods can be problematic. The factor loadings in these models often fluctuate dramatically when markets are under stress, which undermines their reliability. CAPM, on the other hand, offers a simple yet effective way of filtering out market-wide influences, leaving a clearer view of firm-level performance. Its use also ensures direct comparability with recent COVID-19 research, including Albuquerque et al. (2020), where the same approach was adopted. While CAPM may be considered less sophisticated than multifactor frameworks, in this setting its stability and transparency make it a stronger methodological choice. Weekly price range is defined as the difference between the high and low prices per week and was scaled by the midpoint. Weekly price range provides a measure of stock price volatility. The range measure was selected because it better reflects the extremity of market movements that characterised the pandemic period. Standard deviation tends to average out variability, which can obscure the very sharp swings that investors experienced at the time. These two dependent variables for corporate financial performance, weekly abnormal returns and weekly price range, are analysed across three years: 2019, 2020 and 2023.

Control variables. Several firm-specific control variables were included in the analysis to account for potential confounding factors. These include Tobin’s Q, firm size, cash holdings, leverage, return on equity (ROE), return on assets (ROA) and historical volatility. Data for these

control variables were sourced from Compustat for all three years and measured in the preceding year (e.g., for the analysis for 2020, the control variables were measured in 2019). All control variables were Winsorized at the 1% level to mitigate the impact of outliers. Table 1 provides the descriptive statistics, while Table 2 presents the correlation matrices for the three samples 2019, 2020, and 2023.

Table 4-1 Descriptive Statistics

	Observations			Mean			Standard Deviation			25th Percentile			Median			75th Percentile		
	2019	2020	2023	2019	2020	2023	2019	2020	2023	2019	2020	2023	2019	2020	2023	2019	2020	2023
Weekly Abnormal Return	7,696	6,336	8,580	-0.202	-0.055	-0.155	5.967	9.985	4.834	-2.508	-3.782	-2.459	-0.044	-0.071	-0.147	2.167	3.577	2.161
Weekly Price Range	7,696	6,336	8,580	4.529	8.03	4.266	4.348	8.196	3.405	1.841	3.213	2.068	3.353	5.699	3.409	5.882	9.877	5.495
ESG	7,696	6,336	8,580	0.257	0.256	0.255	0.437	0.436	0.436	0	0	0	0	0	0	1	1	1
TobinsQ	7,696	6,336	8,580	1.574	1.683	1.569	1.323	1.231	0.956	0.895	1.017	1.021	1.194	1.321	1.296	1.622	1.773	1.717
Size	7,696	6,336	8,580	6.543	6.319	6.67	2.236	2.472	2.505	5.753	5.579	5.998	6.825	6.88	7.073	7.928	7.947	8.21
Cash	7,696	6,336	8,580	0.092	0.1	0.105	0.14	0.164	0.142	0.013	0.012	0.018	0.042	0.039	0.043	0.093	0.108	0.142
Leverage	7,696	6,336	8,580	0.255	0.282	0.265	0.179	0.197	0.197	0.127	0.126	0.114	0.249	0.279	0.259	0.373	0.407	0.409
ROE	7,696	6,336	8,580	0.021	0.036	0.108	0.303	0.309	0.263	0.004	-0.046	0.02	0.065	0.051	0.097	0.152	0.135	0.189
ROA	7,696	6,336	8,580	0.019	0.009	0.038	0.102	0.127	0.118	0.002	-0.022	0.006	0.029	0.025	0.041	0.063	0.056	0.094
HistoricalVolatility	7,696	6,336	8,580	0.053	0.055	0.059	0.033	0.032	0.024	0.032	0.031	0.04	0.045	0.052	0.058	0.064	0.068	0.073
Dividend	7,696	6,336	8,580	2.438	1.971	2.193	3.231	2.523	2.458	0	0	0	1.171	1.01	1.371	3.8	3.381	3.783

Table 4-2 Correlation Matrices

	Weekly Abnormal Return	Weekly Price Range	ESG	TobinsQ	Size	Cash	Leverage	ROE	ROA	Historical Volatility	Dividend
Correlation Matrix for 2019											
WeeklyAbnormalReturn	1										
WeeklyPriceRange	-0.05	1									
ESG_high	0.01	-0.04	1								
TobinsQ	0.01	-0.08	-0.1	1							
Size	0.01	-0.27	0.31	-0.12	1						
Cash	0.003	0.03	-0.07	0.47	-0.49	1					
Leverage	0.01	-0.15	-0.04	-0.07	0.39	-0.41	1				
ROE	-0.01	-0.12	-0.07	-0.16	0.15	0.01	-0.15	1			
ROA	0.001	-0.21	0.02	0.28	0.37	-0.02	-0.03	0.45	1		
HistoricalVolatility	-0.05	0.31	-0.08	0.13	-0.3	0.01	0.03	-0.43	-0.22	1	
Dividend	-0.003	-0.2	-0.06	-0.13	0.3	-0.26	0.4	0.13	0.11	-0.27	1
Correlation Matrix for 2020											
WeeklyAbnormalReturn	1										
WeeklyPriceRange	-0.07	1									
ESG_high	0.001	-0.05	1								
TobinsQ	0.04	-0.03	-0.04	1							
Size	-0.04	-0.16	0.4	-0.35	1						
Cash	0.04	0.05	-0.11	0.62	-0.56	1					
Leverage	-0.03	-0.08	0.06	-0.19	0.44	-0.46	1				
ROE	0.01	-0.04	-0.11	-0.08	0.09	0.16	-0.14	1			
ROA	-0.04	-0.13	0.1	-0.18	0.44	-0.22	0.15	0.39	1		
HistoricalVolatility	0.03	0.25	-0.17	0.08	-0.44	0.26	-0.25	-0.08	-0.34	1	
Dividend	-0.07	-0.06	0.03	-0.17	0.32	-0.26	0.34	0.14	0.15	-0.37	1
Correlation Matrix for 2023											
WeeklyAbnormalReturn	1										
WeeklyPriceRange	-0.01	1									
ESG_high	0.01	-0.05	1								
TobinsQ	0.01	-0.05	-0.09	1							
Size	0.01	-0.24	0.35	-0.25	1						
Cash	-0.01	0.13	-0.05	0.29	-0.52	1					
Leverage	-0.001	-0.11	-0.03	0.05	0.4	-0.44	1				
ROE	0.03	-0.16	-0.02	0.12	0.33	-0.21	0.21	1			
ROA	0.03	-0.18	0.03	-0.09	0.31	-0.2	-0.11	0.72	1		
HistoricalVolatility	-0.03	0.4	-0.07	-0.03	-0.4	0.23	-0.25	-0.19	-0.25	1	
Dividend	0.01	-0.21	0.13	-0.22	0.33	-0.24	0.22	0.04	0.09	-0.47	1

3.5 COVID-19 Pandemic Time Dummies.

To capture the potential effect and moderating role of fiscal intervention on financial performance, a dummy variable is included in the 2020 specifications. This dummy variable, *postFISCAL*, is measured as 1 for weeks following the fiscal support, and 0 otherwise. Specifically, *postFISCAL* is measured as 1 starting after 2020-03-11 and remains 1 until 2020-09-09. Before the week of 2020-03-11, this dummy variable is measured as 0.

To capture more of the market context during the COVID-19 pandemic, an additional time-related dummy variable is included in the panel data. When COVID-19 cases began to rise in Canada, the dummy variable, labelled as *postCOVID*, was measured as 1, and 0 for weeks prior. Thus, for weeks after 2020-02-19, this dummy is measured as 1, and 0 otherwise.

3.6 Empirical Design.

To analyse the role of ESG performance and economic stimulus on corporate financial performance, pooled regression models were constructed for each year (2019, 2020, and 2023). This methodological approach accounts for the multilevel nature of financial stability, where economic stimulus operates at a macroeconomic level, while ESG performance functions at the firm level. By accounting for these distinct but interrelated topics, our empirical design provides a clearer interpretation for their interactive effects. Two sets of models were constructed. The first is where the dependent variable is weekly abnormal returns, and the second set is for the dependent variable of weekly price range. The independent variables across both sets remained the same. For the 2019 and 2023 model specifications, there are no COVID-19-related time dummies, while in the 2020 specifications, *postCOVID* and *postFISCAL* are added. Further, to capture the potential moderating effect of fiscal intervention between ESG performance and

financial performance, postFISCAL and the ESG dummy are interacted. This is represented in the following models.

For the 2019 and 2023 specifications:

$$FinancialPerformance_{it} =$$

$$\beta_0 + \beta_1 \text{Tobin's } Q_i + \beta_2 \text{Size}_i + \beta_3 \text{Cash}_i + \beta_4 \text{Leverage}_i + \beta_5 \text{ROE}_i + \beta_6 \text{ROA}_i \\ + \beta_7 \text{Historical Volatility}_i + \beta_8 \text{Dividend}_i + \beta_9 \text{ESG}_i + \epsilon_{it}$$

For the 2020 specifications:

$$FinancialPerformance_{it} =$$

$$\beta_0 + \beta_1 \text{Tobin's } Q_i + \beta_2 \text{Size}_i + \beta_3 \text{Cash}_i + \beta_4 \text{Leverage}_i + \beta_5 \text{ROE}_i + \beta_6 \text{ROA}_i \\ + \beta_7 \text{Historical Volatility}_i + \beta_8 \text{Dividend}_i + \beta_9 \text{ESG}_i + \beta_{10} \text{postCOVID}_t \\ + \beta_{11} \text{postFISCAL}_t + \beta_{12} (\text{ESG}_i \times \text{postFISCAL}_t) + \epsilon_{it}$$

4.4 Results

To address our research question regarding what helped ‘immunize’ firms from COVID-induced market volatility, this section presents the results of our analysis on the impact of economic stimulus and ESG performance on financial performance during the COVID-19 pandemic. Each of these years was selected to capture distinct market conditions: 2019 represents the pre-crisis period; 2020 captures the height of the crisis during the pandemic; and 2023 reflects the post-crisis period, where markets had begun to stabilize and return to more typical conditions. For the year 2020, we explored the effects of two important time frames: postCOVID referring to the initial phase of the pandemic, before economic stimulus measures were implemented, and postFISCAL, covering the onset of the government measures.

The results are organized into two main sections: weekly abnormal returns and weekly price range, with each section further divided into findings for each of the three years studied.

Weekly Abnormal Returns

In 2019, the analysis of weekly abnormal returns yielded several insights regarding the factors influencing financial performance in the pre-pandemic context. Our results suggest that ESG performance did not have a meaningful impact on financial performance in the pre-pandemic context, as evidenced by its lack of statistical significance. Specifically, findings from 2019 (model 2) indicated that ESG performance was not statistically significant ($b = -0.034$, $p > 0.1$), indicating that ESG considerations did not meaningfully affect abnormal returns during this period. The R^2 values were very low in both models (model 1: 0.004, model 2: 0.007), indicating that adding ESG to the model did not provide a meaningful improvement in explanatory power, leaving a substantial portion of variance unexplained. This suggests that other factors not captured by these models are likely driving the variance in abnormal returns.

Next, results from the onset of the COVID-19 pandemic in 2020 provide valuable insights into the influence of ESG performance on financial outcomes, as well as the impact of economic stimulus on abnormal returns. The analysis introduces a series of models that incorporate key variables, including ESG, postCOVID, postFISCAL, and ESGxpostFISCAL to examine their individual and combined effects on abnormal returns. In models 3 and 4, the ESG variable represents the average difference in returns between top ESG performers and non-top ESG performers, whereas in models 5 and 6, with the postFISCAL variable added, it captures this difference for the weeks before fiscal intervention. Our findings address Hypothesis 2 in

model 4, indicating that while ESG performance seemed to have a positive effect on financial performance during the pandemic, this relationship did not reach statistical significance ($b = 0.232$; $p > 0.1$). In model 5, the coefficient is unchanged at 0.232, but it rises to 1.143 ($p > 0.1$) in model 6, indicating that before the fiscal intervention, the effect of ESG was positive on average on returns, suggesting potential resilience benefits when combined with economic stimulus. The postCOVID variable had a strongly negative and statistically significant impact on abnormal returns across model 5 and 6 ($b = -4.186$; $p < 0.01$ in both), highlighting the severity of the market volatility, whereas the postFISCAL variable showed a strong positive effect in model 5 and 6 (coefficients = 5.780 and 6.103; $p < 0.01$ in both), highlighting the stabilizing effect of economic stimulus. The inclusion of additional variables in models 5 and 6 highlights the evolving influence of economic stimulus and ESG performance on abnormal returns. The interaction term (ESGxPostFISCAL), which is central to Hypothesis 3, reveals a negative coefficient (-1.262), implying that firms with strong ESG performance may experience a modest reduction in abnormal returns following economic stimulus interventions. However, this effect lacks statistical significance, indicating insufficient evidence to confirm that economic stimulus undermines the ESG performance and financial performance relationship. The R^2 values remained relatively low (model 5: 0.039, model 6: 0.040), indicating that the ESG model did not provide a substantial improvement in explanatory power.

By 2023 (models 7 and 8), market conditions stabilized, prompting our analysis to examine the impact of economic stimulus and ESG performance during the post-pandemic recovery, addressing Hypotheses 1 and 2. ESG performance remained positive but statistically insignificant (model 8, $b = 0.107$, $p > 0.1$), indicating that, while ESG factors may have offered

some stability, their overall effect on abnormal returns was not substantial and could not adequately explain returns in 2023. The findings suggest that during this recovery phase, ESG contributions were not strong enough to drive significant abnormal returns. The R^2 values of 0.003 in both models further highlight that a substantial portion of the variance in abnormal returns remained unexplained, irrespective of ESG inclusion, suggesting that additional factors not captured by these models likely contributed to performance outcomes.

Table 4-3 Pooled Regression Results, ESG Performance Measured as Top Performers in ESG Ratings on Weekly Abnormal Return

	Dependent variable:							
	Weekly Abnormal Returns							
	2019 (1)	2019 (2)	2020 (3)	2020 (4)	2020 (5)	2020 (6)	2023 (7)	2023 (8)
TobinsQ	0.035 (0.066)	0.033 (0.067)	0.012 (0.077)	0.012 (0.077)	0.012 (0.077)	0.012 (0.077)	-0.018 (0.060)	-0.019 (0.060)
Size	-0.026 (0.037)	-0.023 (0.043)	-0.026 (0.036)	-0.053 (0.040)	-0.053 (0.040)	-0.053 (0.040)	-0.008 (0.025)	-0.019 (0.026)
Cash	-0.291 (0.614)	-0.275 (0.609)	-0.189 (0.685)	-0.326 (0.684)	-0.326 (0.684)	-0.326 (0.684)	-0.062 (0.383)	-0.105 (0.377)
Leverage	0.535 (0.462)	0.52 (0.473)	-0.36 (0.590)	-0.301 (0.585)	-0.301 (0.586)	-0.301 (0.586)	0.064 (0.342)	0.107 (0.343)
ROE	-0.700*** (0.231)	-0.711*** (0.236)	0.992* (0.535)	1.054** (0.523)	1.054** (0.523)	1.054** (0.523)	0.32 (0.349)	0.324 (0.345)
ROA	0.669 (0.873)	0.675 (0.870)	-2.737** (1.155)	-2.731** (1.115)	-2.731** (1.115)	-2.731** (1.115)	0.384 (0.801)	0.418 (0.794)
HistoricalVolatility	-10.724*** (2.198)	-10.711*** (2.195)	3.665 (3.102)	3.774 (3.081)	3.774 (3.081)	3.774 (3.082)	-5.613* (3.136)	-5.685* (3.145)
Dividend	-0.031 (0.020)	-0.031 (0.020)	-0.213*** (0.034)	-0.212*** (0.034)	-0.212*** (0.034)	-0.212*** (0.034)	0.019 (0.016)	0.018 (0.017)
ESG		-0.034 (0.149)		0.232 (0.180)	0.232 (0.180)	1.143* (0.673)		0.107 (0.104)

postCOVID					-4.186*** (1.072)	-4.186*** (1.072)		
postFISCAL					5.780*** (1.107)	6.103*** (1.142)		
ESG:postFISCAL						-1.262 (0.878)		
Constant	0.466 (0.356)	0.457 (0.359)	0.562 (0.525)	0.681 (0.539)	-0.121 (0.569)	-0.354 (0.582)	0.069 (0.388)	0.114 (0.387)
Observations	7,696	7,696	6,336	6,336	6,336	6,336	8,580	8,580
R ²	0.007	0.007	0.012	0.013	0.039	0.04	0.003	0.003
Adjusted R ²	0.004	0.004	0.01	0.01	0.036	0.036	0.001	0.001
F Statistic	2.871*** (df = 18; 7677)	2.721*** (df = 19; 7676)	4.425*** (df = 18; 6317)	4.216*** (df = 19; 6316)	12.241*** (df = 21; 6314)	11.873*** (df = 22; 6313)	1.357 (df = 18; 8561)	1.316 (df = 19; 8560)

Note:

*p<0.1; **p<0.05; ***p<0.01

This table reports the results of the pooled regression of weekly abnormal returns on firm characteristics and ESG. There are three respective years included (2019, 2020 and 2023). To get a cleaner estimation for 2020, models 5 and 6 include the dummy variables 'postCOVID' and 'postFISCAL'. 'postCOVID' is a dummy variable which captures when the COVID-19 pandemic had started in Canada, and 'postFISCAL' captures the weeks following fiscal intervention by the Canadian government.

To test the moderating role of the fiscal intervention between ESG and weekly abnormal returns, 'postFISCAL' is interacted with ESG. All accounting variables are Winsorized at the 1% level in each tail. All models include industry dummies. Standard errors are clustered by firm to allow for heteroscedasticity and serial correlation, and are included in parentheses under each coefficient estimate.

Weekly Price Range

The pooled regression results in Table 4 reveal how firm characteristics, ESG performance, and external shocks influenced weekly price range over the periods of 2019, 2020, and 2023.

Beginning with the 2019 period, the analysis of weekly price range generated valuable insights into stock price volatility during the pre-pandemic period. The findings addressing Hypothesis 2 indicate that ESG performance did not significantly affect the weekly price range before the pandemic, as it lacked statistical significance in 2019 (model 2, $b = 0.121$, $p > 0.1$), suggesting minimal impact on price stability during this period. The minimal increase in R^2 when ESG was included indicates that ESG considerations did not significantly enhance the model's explanatory power.

Moving to the height of the pandemic in 2020, the findings provide insights into the effects of economic stimulus on the weekly price range, particularly concerning Hypothesis 3. Like the above models in section 4.1, the model specifications for 2020 included ESG, postCOVID and postFISCAL as dummy variables, and then in model 6, the interaction ESGxpostFISCAL. In models 3 and 4, the ESG variable captures the average difference in weekly price range between top ESG performers and non-top ESG performers throughout 2020. Our analysis addresses Hypothesis 2 through model 4, revealing that ESG performance had a positive and statistically significant effect on price range during the pandemic ($b = 0.731$; $p < 0.1$). These findings do not support Hypothesis 2, as the positive coefficient indicates that ESG performance was associated with increased price volatility rather than an improvement in financial performance during the pandemic. This suggests greater fluctuations in stock prices for

firms with high ESG performance. In model 5, the coefficient is unchanged at 0.731, but it decreases to 0.538 ($p < 0.1$) in model 6, indicating that while the effect of ESG performance on price range continued during the weeks before the fiscal intervention, it weakened slightly. This persistent positive coefficient suggests ongoing price fluctuations among ESG firms. The postCOVID variable, included in models 5 and 6, exhibited a significant positive impact on weekly price range ($b = 12.684$; $p < 0.05$), highlighting the pandemic's impact on volatility, which resulted in significant fluctuations in stock prices across firms. In contrast, the postFISCAL variable in both models 5 and 6, consistent with Hypothesis 1, showed a significant negative effect on price range ($b = -10.397$ and $b = -10.465$, respectively; $p < 0.05$), indicating that economic stimulus was effective in mitigating price volatility, which reflects the stabilizing impacts of governmental support measures. The interaction term (ESG:postFISCAL), which is central to Hypothesis 3, yielded a positive coefficient ($b = 0.267$; $p > 0.1$). This suggests that firms with high ESG performance may experience an increase in price range variability following economic stimulus; however, the lack of statistical significance prevents us from drawing definitive conclusions about the moderating effect of fiscal interventions on the ESG–financial performance relationship. The R^2 values for these models remained relatively low, indicating limited explanatory power of ESG performance in capturing variations in weekly price range. Notably, models 5 and 6 exhibit R^2 values that are approximately double those of models 3 and 4, demonstrating a significant improvement in explanatory power with the inclusion of fiscal intervention variables.

As the market transitioned into recovery in 2023, the previous dynamics of volatility began to evolve, reflecting the changing impacts of economic stimulus and ESG performance

(models 7 and 8). Our analysis explored the impact of economic stimulus and ESG performance during the post-pandemic recovery, addressing Hypotheses 1 and 2 in this context. The coefficient for ESG in 2023 (model 8) was negative but statistically insignificant ($b = -0.063$; $p > 0.1$), implying that ESG factors did not significantly impact the weekly price range during the recovery phase. Furthermore, the minimal R^2 increase when ESG was included suggests that ESG did not add to the explanatory power of the model.

Table 4-4 Pooled Regression Results, ESG Performance Measured as Top Performers in ESG Ratings on Weekly Price Range

	Dependent variable:							
	Weekly Abnormal Returns							
	2019 (1)	2019 (2)	2020 (3)	2020 (4)	2020 (5)	2020 (6)	2023 (7)	2023 (8)
TobinsQ	-0.282*	-0.275*	-0.254	-0.253	-0.253	-0.253	-0.305***	-0.304***
	(0.145)	(0.145)	(0.192)	(0.193)	(0.193)	(0.193)	(0.085)	(0.085)
Size	-0.250***	-0.264***	-0.202**	-0.287***	-0.287***	-0.287***	-0.114***	-0.108***
	(0.074)	(0.074)	(0.081)	(0.096)	(0.096)	(0.096)	(0.039)	(0.041)
Cash	-1.356	-1.411	1.186	0.754	0.754	0.754	0.474	0.499
	(0.951)	(0.960)	(1.875)	(1.876)	(1.877)	(1.877)	(0.553)	(0.552)
Leverage	-1.311*	-1.256*	1.650*	1.836*	1.836*	1.836*	0.385	0.36
	(0.752)	(0.736)	(0.988)	(0.980)	(0.980)	(0.980)	(0.466)	(0.472)
ROE	0.302	0.34	0.479	0.675	0.675	0.675	0.031	0.028
	(0.640)	(0.650)	(0.539)	(0.520)	(0.520)	(0.520)	(0.404)	(0.404)
ROA	-3.864**	-3.886**	-2.950*	-2.933*	-2.933*	-2.933*	-2.089*	-2.109*
	(1.540)	(1.538)	(1.791)	(1.742)	(1.742)	(1.742)	(1.079)	(1.081)
HistoricalVolatility	29.072***	29.025***	45.377***	45.722***	45.722***	45.722***	44.239***	44.281***
	(7.403)	(7.479)	(13.647)	(13.300)	(13.302)	(13.303)	(6.300)	(6.325)
Dividend	-0.065*	-0.063*	0.083	0.089	0.089	0.089	-0.061*	-0.060*
	(0.037)	(0.038)	(0.078)	(0.075)	(0.076)	(0.076)	(0.034)	(0.034)
ESG		0.121		0.731**	0.731**	0.538		-0.063
		(0.238)		(0.359)	(0.359)	(0.488)		(0.137)
postCOVID					12.684***	12.684***		

					(0.672)	(0.672)		
postFISCAL					-10.397***	-10.465***		
					(0.582)	(0.595)		
ESG:postFISCAL						0.267		
						(0.406)		
Constant	5.923***	5.956***	5.094***	5.471***	2.763*	2.812*	2.977***	2.951***
	(0.933)	(0.931)	(1.514)	(1.547)	(1.550)	(1.546)	(0.674)	(0.680)
Observations	7,696	7,696	6,336	6,336	6,336	6,336	8,580	8,580
R ²	0.189	0.189	0.097	0.098	0.245	0.245	0.179	0.179
Adjusted R ²	0.187	0.187	0.095	0.095	0.242	0.242	0.178	0.178
F Statistic	99.264*** (df = 18; 7677)	94.089*** (df = 19; 7676)	37.744*** (df = 18; 6317)	36.186*** (df = 19; 6316)	97.446*** (df = 21; 6314)	93.022*** (df = 22; 6313)	103.959*** (df = 18; 8561)	98.508*** (df = 19; 8560)

Note: * p<0.1; ** p<0.05; *** p<0.01

This table reports the results of the pooled regression of weekly price range on firm characteristics and ESG. There are three respective years included (2019, 2020 and 2023). To get a cleaner estimation for 2020, models 5 and 6 include the dummy variables 'postCOVID' and 'postFISCAL'. 'postCOVID' is a dummy variable which captures when the COVID-19 pandemic had started in Canada, and 'postFISCAL' captures the weeks following fiscal intervention by the Canadian government.

To test the moderating role of the fiscal intervention between ESG and weekly abnormal returns, 'postFISCAL' is interacted with ESG. All accounting variables are Winsorized at the 1% level in each tail. All models include industry dummies. Standard errors are clustered by firm to allow for heteroscedasticity and serial correlation, and are included in parentheses under each coefficient estimate.

4.5 Conclusion

The COVID-19 pandemic prompted a significant response from governments globally, with G7 countries and others spending trillions of dollars to stabilize markets. This study provides valuable insights into firm resilience during the pandemic, particularly regarding the comparative roles of economic stimulus and ESG performance in stabilizing firm outcomes amid market volatility. We employ slack resource theory and good management theory to explain how slack resources, such as fiscal space, interact with effective management practices to influence firm performance during market volatility. Specifically, this research tested three hypotheses to evaluate the distinct and combined effects of economic stimulus and ESG performance in stabilizing firm outcomes. Our results demonstrate how these factors affected weekly abnormal returns and weekly price ranges throughout the pre-pandemic (2019), pandemic (2020), and post-pandemic (2023) periods, providing a comprehensive timeline for the analysis. Our findings challenge the widely held view (e.g., Albuquerque et al., 2020; Lins et al., 2017) that superior ESG performance ‘immunized’ firms against crisis impacts. Instead, our findings align more closely with the conclusions of Demers et al. (2021), which highlight the importance of financial and economic fundamentals in determining firm resilience during crises.

Revisiting our research question: How does economic stimulus compare and interact with ESG performance in stabilizing financial performance during COVID-induced market volatility? Our findings, using slack resource theory and good management theory, suggest that economic stimulus played a significantly larger role than ESG in stabilizing financial performance. This highlights the importance of a multilevel analysis, where macroeconomic policies (e.g., economic stimulus) serve as external stabilizers. These results highlight the intricate relationship

between government interventions and firm sustainability strategies, supporting our methodological choice for a comprehensive approach to sustainable finance research. Specifically, in addressing Hypothesis 1, we found that the Canadian government's substantial fiscal capacity enabled the deployment of broad economic stimulus, providing essential liquidity that allowed firms to endure the volatile environment. Canada's indiscriminate fiscal approach reduced financial differentiation among firms, consequently disrupting typical market mechanisms, irrespective of their ESG performance. This intervention fundamentally altered market dynamics, overshadowing both financial and non-financial factors, with government actions replacing market self-regulation (Malkiel, 1991). This perspective resonates with Keynesian economic principles, which emphasize fiscal interventions in stabilizing markets and ensuring operational continuity during periods of significant economic uncertainty (Makin & Layton, 2021).

In contrast, our findings indicate that ESG performance alone was insufficient to stabilize firms throughout the pandemic. While ESG initially contributed positively to financial performance before government interventions, this effect diminished following the economic stimulus, as suggested by the interaction effects. Similarly, ESG was associated with reduced price volatility in early pandemic periods, yet this stabilizing effect diminished post-stimulus. These findings address Hypothesis 2, showing that ESG performance did not meaningfully contribute to financial stability during the pandemic. This supports the findings of Duque-Grisales and Aguilera-Caracuel (2021), who argue that financial slack may weaken the ESG-financial performance relationship, therefore reducing the typical financial benefits of high ESG

performance. Thus, indiscriminate fiscal support weakened the competitive advantage held by ESG-leading firms.

Fiscal intervention played a dual role by both averting economic collapse and reducing ESG-based differentiation, ultimately blurring the competitive advantage traditionally held by ESG-strong firms, as noted by Albuquerque et al. (2020). Our evidence supports Hypothesis 3, showing that economic stimulus diminished the competitive advantages linked to ESG performance by acting as an institutional equalizer. When examining interaction effects, economic stimulus blurred distinctions between ESG-strong and ESG-weak firms. Although ESG-focused firms exhibited some resilience, the liquidity support available to all firms mitigated what could have otherwise been a significant difference between ESG and non-ESG performance. This outcome aligns with slack resource theory and the principle of competitive neutrality, suggesting that fiscal intervention provided external slack that equalized firm-level differences, as noted by Duque-Grisales and Aguilera-Caracuel (2021).

Our research contributes theoretically by extending slack resource theory to incorporate fiscal space, demonstrating that government interventions function as critical moderating factors during crises. This extension broadens the scope of slack resource theory while complementing good management theory by illustrating how effective management utilizes slack resources to navigate through volatility. Unlike traditional management theories focused on internal resilience, our findings highlight the role of external interventions in stabilizing markets and ensuring firm survival. By positioning fiscal space as a mechanism for reallocating resources to meet immediate market needs, we demonstrate its function as a mediating factor in managing crisis-induced volatility. This addresses a key gap in the literature, which often overlooks the

importance of macro-level policy interventions during periods of extreme market stress. To enhance the understanding of this interplay, our work provides a nuanced perspective on the relationship between government policy, managerial practices, and firm resilience, emphasizing that both internal strategies and external fiscal measures are necessary to navigate severe market instability effectively.

While our study offers significant contributions to the debate on ESG and financial performance, it is not without limitations. One notable limitation involves the relatively low R^2 values in our models, suggesting that other factors may significantly impact financial performance. Additionally, focusing exclusively on the Canadian context restricts the generalizability of our findings, as differing fiscal and monetary policies in other regions could lead to divergent outcomes. Future research should address these limitations by expanding the sample size, incorporating more diverse industries, and exploring varied regional contexts to enhance the robustness and generalizability of these findings. By addressing these limitations, future research can build on our findings to provide a more comprehensive understanding of the factors that contribute to firm resilience in times of crisis.

Chapter 4 examined the relationship between firm-level ESG performance and macroeconomic fiscal stimulus, showing that while stimulus acted as a broad stabilizer, it also diminished the differentiating role of ESG during the crisis. These findings reinforce the need to interpret corporate resilience not only through internal capabilities but also in relation to external systemic interventions. Chapter 5 builds on this by drawing together the insights from earlier chapters, positioning them within the broader theoretical frame of social innovation, and reflecting on their implications for sustainable finance research and practice.

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5. CONCLUSION

Climate change continues to pose significant challenges globally (WEF, 2024). Consequently, corporations and state actors have faced scrutiny for their contributions to the escalating anthropogenic pressures on our biosphere. Within the global community, many have turned to social innovations, particularly AI, as a potential solution to better comprehend, enhance, or alleviate the challenges posed by climate change and sustainability. Recognizing the potential of AI in addressing these complex issues, efforts are being made to leverage its capabilities to gain deeper insights, improve decision-making processes, and facilitate sustainable finance practices. Similarly, ESG practices can be viewed as an adjacent social innovation aimed at progressing and measuring firms' progress towards the SDGs.

For AI for sustainable finance to effectively contribute to the advancement of sustainable development, it is imperative to consider not only the envisioned benefits perceived by their developers, but also the accessibility, utility, and integration of such technologies and practices within diverse contexts that encompass economic, political, and cultural variations. While AI can be conceptualized as a social innovation in its capacity to affect positive systemic change (Westley, 2014), ESG is better understood as a framework that guides decision-making rather than innovation itself. The COVID-19 crisis further emphasizes this distinction, revealing ESG's limited adaptability during periods of market volatility.

AI for sustainable finance has demonstrated some potential to enhance the quality of life in developing nations, enabling broader access to essential resources and amenities for their inhabitants. Nonetheless, it is crucial to acknowledge that the unregulated nature of AI for

sustainable finance, falling outside the purview of conventional financial regulatory frameworks, may introduce adverse impacts on financial markets or perpetuate exclusionary practices for those lacking access (Pashang & Weber, 2021). Consequently, society finds itself engaged in lively debates regarding the implications of AI in hopes to forge a viable path towards, shedding light on the nuanced nature of social innovation. These debates increasingly centre on tangible outcomes such as reductions in CO₂ emissions and broader environmental impacts that determine whether technological advances genuinely contribute to sustainable development (Pashang & Weber, 2023). Such tensions strike a resemblance to the historical progression of other social innovations that have come before. While the potential of leveraging AI for sustainable finance has attracted attention, the precise mechanisms and implications of this intersection are not yet comprehensively understood. A significant void exists within academic research pertaining to both societal and institutional approaches in the context of sustainable finance and AI.

In chapters 3 and 4, ESG's role as a social innovation has shown inherent limitations, particularly in the context of the pandemic crisis. While ESG was originally designed to integrate sustainability into corporate practices, its limited scalability and adaptability under crisis conditions highlight the need for significant re-evaluation and reimagining to address systemic disruptions effectively, particularly in ensuring meaningful sustainability outcomes.

Notwithstanding the notable contributions of previous works (e.g., Demers et al., 2021) in this domain, our research serves as a pioneering effort, making novel contributions that shed light on the far-reaching implications of the COVID-19 pandemic. The significance of this research lies not only in its ability to add to the existing body of knowledge but also in its capacity to pave the way for future research endeavors. By addressing the pressing issues surrounding sustainable

finance, AI, and the pandemic, this study sets the stage for further scholarly exploration, enabling a more comprehensive understanding of the transformative potential and challenges that lie ahead.

5.1 Contribution to Knowledge

This dissertation represents a noteworthy addition to the existing body of knowledge concerning sustainability management, particularly in the context of sustainable finance and the role of AI, with ESG positioned as an adjacent social innovation. Through comprehensive research and analysis, this scholarly work introduces a range of novel insights and contributions that enrich the field. Guided by the research questions, the contribution of this research is multifold in addressing the role of AI in sustainable finance.

First, we emphasize that the study of AI for sustainable finance is new and has received little (but growing) attention in the literature, which leaves it undertheorized, with unsettled terminology and definition. Moreover, as Geobey (2014) states, it is largely practitioner-driven, often characterized by evangelistic attitudes rather than critical analyses. We address these gaps by investigating existing governance mechanisms that Canada and other G20 nations have in place with regard to AI for sustainable finance. We do this by highlighting the role and implications of AI for sustainable finance in relation to the SDGs. Further, we consider two vantage points related to AI for sustainable finance, the first being at the institutional level in the context of ESG ratings, and the second, at the societal level in the context of digital financial inclusion. Finally, we provide timely discussions about the COVID-19 pandemic and the various risks and opportunities it presented in the context of AI for sustainable finance. In each focus

area, we identify key governance challenges, and accordingly, present key policy recommendations for multi-stakeholders in academia and industry.

Second, we make several notable empirical contributions to AI for sustainable finance by highlighting the comparative value of insights derived from AI-generated public sentiment data in contrast to conventional ESG ratings during times of crisis, which largely remains unexplored. This inquiry is particularly notable due to the evolving and inconclusive nature of the understanding of the relationship between ESG and financial performance within the academic community, particularly during crises. From an empirical view, examining the relationship of ESG performance of firms during crisis is a challenge due to the utilization of conventional ESG data. Further, the abruptness and speed at which the COVID-19 pandemic unfolded have not been captured in such ESG data. Our research asserts that during the COVID-19 pandemic, AI-generated public sentiment data correlates more strongly with financial returns and market volatility during this crisis than conventional ESG data. This suggests that AI-generated data (with specific COVID-19 sub-signals) not only capture a broader range of variables that affect financial performance but also reflects market conditions more rapidly than conventional ESG data. Given recent advancements in AI as well as debates and scrutiny surrounding ESG data quality by various stakeholders, this research is timely and contributes to the growing debate about measuring ESG performance.

Third, the dissertation explores the critical role of financial factors, such as economic stimulus, slack resources, and foundational economics, in stabilizing firm performance during the pandemic. Findings corroborate seminal works (e.g., Demers et al., 2021), challenging early assumptions that ESG performance inherently provided resilience. Instead, this study emphasizes

the importance of economic stimulus in mitigating market volatility, offering a nuanced understanding of the interplay between financial mechanisms and sustainability metrics.

Fourth, novel methodological contributions were made in chapter 3, as evidenced by the data and results, which empirically examined how AI-generated public sentiment ratings compare to conventional ESG data in offering material insights. While numerous studies have since examined the relationship between ESG performance and financial performance, there is limited scholarly research comparing the efficacy of AI-generated public sentiment data to traditional ESG data. Our results demonstrate that during crises, AI-generated public sentiment ratings can serve as a stronger proxy for stakeholder satisfaction by offering real-time pandemic insights, which enable a deeper understanding of dynamic materiality. This methodological contribution enhances the tools available to researchers and practitioners for evaluating sustainability metrics in volatile environments.

Finally, our research is the first of its kind to examine the relationship of ESG performance and financial performance of Canadian firms during the pandemic. While extant literature has examined this relationship since the advent of the crisis, to our knowledge, this study integrates AI-generated insights, offering a novel perspective on how AI-driven public sentiment and ESG factors influence firm resilience. Chapter 3 specifically explores how AI-generated public sentiment ratings serve as a proxy for stakeholder satisfaction, offering real-time insights into financial performance. This aligns with research by Serafeim (2020) and Macpherson and Gasperini (2021), who showed that AI can ESG risks and opportunities more dynamically than conventional ESG ratings. In Chapter 4, we extended this analysis by examining the comparative role of ESG performance and economic stimulus in firm resilience,

emphasizing how macroeconomic policies can shape firm strategies (Flammer & Ioannou, 2021; Ramelli & Wagner, 2020). By bridging these insights, this study contributes to the discourse on AI as a social innovation (Calzada, 2024; WEF, 2024), demonstrating its potential to enhance sustainable finance through such insights. Due to the void in the overlap between domains such as sustainability, finance, and AI during the COVID-19 pandemic, this research creates new space for this and future works by filling the void with exploration and empirical findings.

5.2 Contribution to Theory

This dissertation contributes to the growing field of AI for sustainable finance while advancing the understanding of social innovation within the field of sustainability management. By employing social innovation theory, this research highlights the roles of AI and ESG practices, each distinct and independently significant. This framing critically examines their potential and limitations in addressing sustainability challenges, particularly during crises such as the COVID-19 pandemic. Sustainability management, as a transdisciplinary school of thought, benefits from integrating theoretical perspectives that address complex socio-ecological contexts effectively. This dissertation emphasizes the importance of utilizing theories that reflect the interconnected dynamics of sustainability, finance, and innovation, encouraging the development of multidimensional frameworks.

Theories like good management theory and slack resource theory (Waddock & Graves, 1997) are also extended and refined through this research. Good management theory traditionally emphasizes stakeholder satisfaction as a means to improve financial performance. This dissertation incorporates AI-generated public sentiment data as a novel proxy for stakeholder satisfaction, showing how it captures dynamic materiality and correlates more strongly with

financial returns and market volatility during crises compared to conventional ESG data. These findings suggest that AI-driven insights address the limitations of traditional management tools, providing real-time adaptability that is critical in volatile market conditions.

Similarly, slack resource theory is reimagined through the integration of fiscal space, which acts as a moderating factor during crises. Findings from chapter 4 demonstrate how government interventions, such as fiscal stimulus, create slack resources that firms can leverage to maintain resilience and stability. This research broadens slack resource theory to include the role of external economic stimuli, illustrating how effective managers navigate resource allocation during market disruptions. By framing fiscal space as a mechanism for enabling adaptive capacity, this study offers a useful expansion of slack resource theory, making it relevant to the real-world demands of sustainable finance during crises.

This dissertation also critiques ESG practices as a social innovation. While ESG conceptually aligns with social innovation theory, findings from chapters 3 and 4 reveal significant limitations in its scalability and adaptability during crises like the COVID-19 pandemic. ESG's reliance on static, retrospective data impedes its ability to achieve transformative outcomes in volatile conditions. According to Westley's (2014) framework, successful social innovations are characterized by durability and adaptability, qualities that ESG practices fail to meet in their conventional form. This limitation highlights the need for reimagining ESG practices to ensure they can effectively respond to the evolving demands and complexities of sustainable finance.

Building upon the seminal works by Westley (2014) and Cajaiba-Santana (2014), this dissertation operationalizes core concepts such as durability, scale, and transformative impact to

assess AI as a social innovation. AI's adaptability and ability to generate real-time insights during crises are contrasted with ESG's challenges in achieving similar transformative outcomes under volatile and uncertain conditions. For instance, findings from chapter 3 highlight that AI-generated public sentiment data provides near real-time insights into market dynamics, demonstrating both scalability and responsiveness during crisis periods. These qualities align with the durability and adaptability expected of successful social innovations as outlined in Westley's (2014) framework. ESG, on the other hand, as detailed in chapters 3 and 4, struggled to scale effectively during the COVID-19 pandemic due to its reliance on static and retrospective data, limiting its ability to maintain relevance and adaptability during volatility.

This research draws from social innovation theory within the dissertation. It advances the discourse by critiquing and extending foundational theories while demonstrating how AI functions as a social innovation during crises. By framing these insights through the lens of sustainability management, this study offers a cohesive, evidence-based approach to addressing the complexities of sustainable finance and contributing to the development of more adaptable and impactful practices for future crises.

5.3 Future Research Directions

Regarding social innovations in institutional sustainable finance, this research highlighted the potential of AI advancing progress towards the SDGs, particularly during crises such as the COVID-19 pandemic. By addressing a critical gap in the research, that access to real-time financial and non-financial insights can enable stakeholders to make 'good' decisions during the COVID-19 pandemic. However, there remains a substantial gap in sustainable finance literature

on the efficacy of such innovations as it relates to non-pandemic crises, AI techniques and data quality, and sector and geographical scope.

Also, there is little evidence about whether AI-generated public sentiment data can be a suitable alternative to conventional ESG data during non-pandemic periods or non-pandemic crises. This addresses a fundamental gap in both practice and research about how conventional ESG data and methodologies compare to AI alternatives in providing useful insights to stakeholders who navigate market volatility. Future research should examine the role of ESG performance and AI-generated public sentiment beyond health pandemics, to include natural disasters, geo-political instability, or corporate wrongdoings. Exploring how these factors influence financial performance and risk reduction during these events could shed light on the consistency of ESG performance and AI-generated public sentiment data as proxies for stakeholder satisfaction. Moreover, scholars can compare whether economic stimulus or ESG performance helps provide firms with greater resilience during market volatility caused by other crises.

To address methodological challenges associated with AI-generated insights such as data quality, data volume, algorithm biases, we encourage future research to extend the temporal scope of data collection, with the aim of assessing the robustness of the findings. Further, as our study in chapter 3 employs ESG data from 2019, future research can source 2020 (and beyond) data to help determine whether ESG vendors adjusted or revised their data or methodology in the wake of a pandemic. Additionally, future research could compare techniques and data developed by AI data providers, and other conventional ESG providers that now use AI into their ratings. Scholars could also develop their own proprietary AI algorithms and compare with AI and non-

AI vendors. This could allow researchers to see how they converge or diverge in their insights related to data volume, bias, and accuracy. Future research may explore the use of recent innovations such as GenAI and LLMs. For example, how might these tools address algorithmic biases, expand or limit the inclusivity of digital financial systems, or introduce new forms of agentic behaviour in how technologies make, or appear to make, autonomous financial and sustainability-related decisions?

Finally, acknowledging the heterogeneous impacts of the pandemic across different economies, markets, and industries, researchers may also find value in examining the efficacy of AI for sustainable finance to assess the universality of our findings across different global contexts. The pandemic revealed significant disparities in how firms and markets responded to disruptions, emphasizing the need for nuanced, context-specific insights. For example, chapter 4 discussed the differential effects of economic stimulus measures across sectors, highlighting the importance of methodological experimentation. Research could evaluate how AI for sustainable finance functions across diverse global contexts, determining whether the insights generated in this study are scalable or require region-specific adaptations. Additionally, there is scope to explore how AI could be applied beyond finance, in sectors such as healthcare, energy, or transportation, particularly in advancing sustainability objectives. Such investigations could identify help establish nuanced, geographically specific guidelines and actionable frameworks for its integration into sustainable practices.

5.4 Practical Implications

We revisit the concept of techno-solutionism, which reveals social innovation as a double-edged sword, whereby one can no longer discuss its benefits without addressing its

drawbacks (Pashang & Weber, 2023). This research demonstrates the need for a multidisciplinary and multistakeholder approach, particularly during crises, to maximize the potential of such social innovations while mitigating their risks. In line with the SDGs, key stakeholders across sectors and end-users who utilize these social innovations should be actively involved in this dialogue to continue addressing not only the benefits, but also the contradictory, unintended, or unexpected consequences.

Empirical findings of this research suggest that AI holds promise for stakeholders in institutional sustainable finance, particularly during times of crisis. However, this promise depends not only on the availability of advanced tools, but also on the governance structures, ethical safeguards, and collaborative processes that guide their use. The responsibility therefore lies less in the technologies themselves and more in the ways societies, firms, and regulators choose to mobilize them.

By situating AI and ESG within social innovation theory, this thesis shows that the future of sustainable finance will depend less on technological potential alone and more on the collective capacity to govern, adapt, and mobilize these innovations under conditions of uncertainty. This closing reflection highlights the urgency for transparent, inclusive, and systemic approaches to ensure that AI and ESG contribute meaningfully to resilience, equity, and sustainable development.

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APPENDIX

Table A1

Variable Definitions and Data Sources

Variable	Definition	Data Source
BHAR	Abnormal buy-and-hold returns were estimated using the CAPM model, with betas being estimated using a 52-week estimation window from 2019 using weekly returns. Expressed as a percentage.	Compustat
Median Scaled Range	The median of weekly price ranges.	Compustat
Weekly Abnormal Return	Weekly abnormal return is the difference between the weekly logarithm return of a stock and the CAPM beta multiplied by the weekly logarithm return of the market, expressed as a percentage. The CAPM beta per firm is estimated using a 52-week estimation window from 2019 using weekly returns. Expressed as a percentage.	Compustat
Weekly Price Range	Weekly high minus low price range of a stock, scaled by the midpoint of the weekly high and low prices. Expressed as a percentage.	Compustat
ESG (ESG, ENV, GOV, SOCIAL)	ESG-related scores for ESG (composite), ENV (the Environmental Pillar), GOV (the Corporate Governance Pillar), and SOCIAL (the Social Pillar), measured in 2019 and measured from 0 to 100.	Refinitiv
TobinsQ	Book value of assets (AT) minus the book value of equity (CEQ) plus the market value of equity (CSHO x PRCC), all divided by the book value of assets (AT), measured in US currency for 2019.	Compustat
size	Natural log of firm sales (SALE) plus one, measured in US currency for 2019.	Compustat
cash	Cash (CHE) over book assets (AT), measured in US currency for 2019.	Compustat
leverage	Book value of debt (DLTT + DLC) divided by assets (AT), measured in US currency for 2019.	Compustat
Return on equity (ROE)	Net income (NI) divided by book equity (CEQ), measured in US currency for 2019.	Compustat
dividend	Dividend per share (DVPSX) divided by stock price at the end of the year (PRCC), multiplied by 100, measured in US currency for 2019.	Compustat

historical volatility	Volatility, using the standard deviation of the weekly logarithm return of a stock during 2019.	Compustat
netSignals	Weekly net (cumulative sum) of all five sub-signals (below), per firm. Measured from the week starting on January 8 th , 2020, to September 9 th , 2020. Measured on a scale from -20 to +20. For the cross-sectional models, netSignals is the average of the weekly measurement of netSignals, per firm.	Truvalue Labs
Sub-signals (labour, supplyChain, response, economy, socialImpact)	Weekly public sentiment rating per firm. The respective sub-signals are defined in Table 1. Measured from the week starting January 8 th , 2020, to September 9 th , 2020. Measured on a scale from -20 to +20. For the cross-sectional models, sub-signal ratings are the average of the weekly respective sub-signal measurements, per firm.	Truvalue Labs