SUSTAINABILITY EVENTS AND OPERATIONS PERFORMANCE: EVENT STUDY, EVENT MINING, AND DATA-DRIVEN EVENT ANALYTICS

XU MINGZE

PhD

The Hong Kong Polytechnic University

2023

The Hong Kong Polytechnic University
School of Fashion and Textiles

Sustainability Events and Operations Performance: Event Study, Event Mining, and Data-driven Event Analytics

Xu Mingze

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

December 2022

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

____________________ (Signed)

Xu Mingze ____________ (Name of Student)

ABSTRACT

The fashion industry is facing sustainability challenges due to the pollution it creates and the nature of its energy- and resource- intensive operations. Researchers and managers are increasingly being urged to develop proactive sustainability strategies to meet the expectations of stakeholders and to cope with the challenges sustainability poses in the ever-changing business environment. Stakeholders are expecting firms to be more transparent in their sustainability activities, by adopting practices such as sustainability reporting. However, due to a lack of understanding of the value of sustainability reporting, many companies remain in a dilemma about whether and when to produce sustainability reports, which involve voluntary reporting that is beyond mandatory requirements. Apart from the pressure to meet stakeholder expectations, firms face many challenges from events taking place in the business environment that can influence their operations, supply chain activities, and competitiveness. These can not only challenge individual firms but also the wider industry and market development. In view of these expectations and challenges, this thesis offers innovative solutions to address this rapidly changing environment with the aim to help managers make decisions. Insights are gained from conducting three studies, with the results reported herein.

The first study examines whether and when sustainability reporting can improve the performance of manufacturing firms based on signaling theory and stakeholder theory. The extant literature shows that sustainability reporting (SR) can improve a firm's market and financial performance through signaling its superiority to external stakeholders (investors and customers); this is known as the costly signaling effect. However, less is known about how internal stakeholders, like operations employees and senior management, can use SR to improve operational efficiency. We hence conducted five event studies to estimate the abnormal performance of US reporting and non-reporting manufacturers using Global Reporting Initiative (GRI) standard data from 1999–2020, which included 1254 firm-year observations. The findings suggest there are time-lagged positive effects of GRI reporting on the abnormal return on assets (ROA), *labor productivity*, COGS/*Sales*, *Tobin's q* (short term), and *market value* (marginal) due to the costly signaling (i.e., GRI reporting). Furthermore, by

using *media exposure*, *first-time reporting*, and *reporting frequency* as proxies for *signal observability*, our regression results show that they can improve profitability, in terms of the abnormal ROA, and operational efficiency, in terms of *labor productivity*, through a "reverse" signaling effect. However, these proxies fail to improve *market value* and COGS/*Sales*, suggesting some weaknesses in the signaling effects. These results suggest that executives should pay more attention to internal stakeholders (employees) and sustainable operations when investing in GRI reporting. This study fills the research gap about the role of SR in driving financial performance and productivity, grounded in the integrated framework of stakeholder theory and signaling theory.

As observed through the process of conducting the first study, there are limitations in conducting event studies. We observe that, in order to gain an understanding of an event and how it may affect firms, event identification is the beginning and indeed the most important step. Currently, this is still a manual process that relies heavily on the researcher's efforts, leading to several limitations in terms of efficiency, capacity, and comprehensiveness with respect to gaining insights on events that occur at high frequencies in the market. In particular, the existing event studies approach is to focus on a single event, which is an unrealistic scenario and fails to take into account the actual complexities of the business environment. To address these limitations, in Study 2, we designed and developed an approach called *EventMining* to identify multiple event clusters from textual company data available online. This approach adopts Natural Language Processing (NLP), which is a mainstream element of Artificial Intelligence (AI) technologies. The *EventMining* approach can help researchers and managers automatically collect, pre-process, analyze, and identify multiple event cases. Using company news collected from Thomson Reuters, we demonstrate that multiple event cases can be identified by *EventMining* and with less researcher intervention needed. By focusing on multiple event cases and replacing previous manual work, the proposed *EventMining* approach advances event study methods in terms of event identification. Based on four designed modules, *EventMining* collects, preprocesses, and analyzes textual data and eventually identifies event cases. Our application of the proposed approach to company news demonstrates its utility and robustness. To the best of our knowledge, *EventMining* is among the first efforts in machine-based event identification and event case generation. The proposed approach contributes to gaining an understanding of the event patterns contained in complex text data.

In a volatile, uncertain, complex, and ambiguous market, managers have to adapt and respond to events as they arise in the business environment. While sustainability events are an important stream of events that now concern managers and stakeholders, less attention has been paid so far to Emerging Sustainability Events (ESEs), which are sustainability events that are still in the formation process. Although the use of *EventMining* in the second study provides a tool for managers to identify multiple event cases in their business environment, the question remains as to what are the important events that might trigger market reactions. In Study 3, we employ the *EventMining* approach and extend Study 2 with the design of a data-driven event analytics system. Based on a large-scale event study including 120 ESEs, our empirical findings show that a series of ESEs can trigger market reactions. Unlike the event study literature hypothesized general effects of events, we find that ESEs may have localized effects that can affect specific groups of firms. Abnormal returns can indicate investors' concerns about ESEs. The results also highlight the most important ESEs concerning investors. To the best of our knowledge, this study is among the first to highlight the importance and impact of ESEs for gaining managerial insights. This study sheds light on the role of emerging events in prompting managers to develop proactive strategies and operations.

ACKNOWLEDGEMENTS

Life is not linear, and neither is a PhD. Like the line I wrote on my first academic resume – There is no royal road to research. There would be a rocky road for me. In any situation, you can do better, step by step.

I would like to express my gratitude to my chief supervisor, Prof. Christina WY Wong. This dissertation would not have been possible without her kind support. I appreciate her unstinting and tireless training and supervision. Her comments provided me with a lot of guidance. Her meticulous review and feedback helped me a lot to describe, to write, and eventually to formulate this dissertation and the research papers. I would also like to thank Prof. Chee Yee Wong and Prof. Sakun Boon-itt, who offered delicate reviews and revisions to the research work to improve the quality, as a research team.

Prof. Kevin Linderman has also been an exceptional mentor. Although the unexpected pandemic affects many things, including my visiting plan at Minnesota and Penn State, I am lucky to conduct research with him and receive his mentoring, which is important to me to keep my passion for pursuing research. I would like to thank him for investing in me and I hope to use the skills I learned from him to achieve the goal of doing solid research work.

My appreciation extends to Prof. Huajun Tang and Prof. Ivan Lai, for their helpful guidance and support for my PhD journey beyond my master's dissertation. I would like to thank Dr. Yangqiu Song for his meaningful advice about natural language processing knowledge at HKUST. I owe a deep sense of gratitude to my research colleagues, Dr. Di Fan, Mr. Junda He, Prof. Hugo Lam, Dr. Magnum Lam, Dr. Bruce Tong, Dr. Eric Xu, Mr. Peter Zhang, and Dr. Paul Zhou. Their generous support and encouragement help me walk through the PhD journey.

My sincere thanks went to the faculty members in my school. Prof. Jason Choi helped me a lot through his mentoring and suggestions. I would like to thank Dr. Chole Ki and Dr. Chris Lo, for their valuable comments and suggestion as my PhD registration committee. I want to thank Prof. Xenophon Koufteros and Prof. Giri Kumar Tayi, for their comments and suggestions on the research works during their visits at PolyU. I would like to thank Dr. Wing-sun Liu for his advice and kind support in my teaching work. I would also like to thank the department colleagues at PolyU School of Fashion and Textile (Institute of Textile and Clothing), PolyU Business School, PolyU Computing and HKUST Computer Science and Engineering for their support and help in registration, resources and administration. Special thanks went to Ms. Sicily Ho, Ms. Lemona Kong and Ms. Tracy Wu for their kind help and support. I would like to thank my group and office mates, Dr. Can Gao, Dr. Junjun Fan, Dr. Chunsheng Li, Dr. Su Liu, Mr. Xianjing Liu, Dr. Yingyi Liang, Dr. Dongmei Mo, Ms. Xu Pan, Dr. Jianjun Qian, Dr. Tingting Tian, Dr. Yihui Tian, Dr. Yingjia Wang, Dr. Jie Zhou, and Dr. Xingxing Zou, for the joy and life stories shared with me while working on research projects.

I also appreciate the collaborative team at the PolyU student affairs office for the four-year tutorship journey. Thank you, Mr. Ivan Chung, Dr. Andrew Chu, Prof. Jinsoo Lee, Dr. Howard Kwong, Ms. Grace Tang, Dr. Eric Tam and Prof. Esmond Mok. I would also thank all my tutor colleagues, friends, helpers and residents at Boyan Hall, Yellow Hall and Lizhi Hall for their wonderful support.

Last but not least, I would like to thank my family for their warm support during my PhD study. I am indebted to them for their unconditional love and care. Although they were not involved in the research experiments directly, their incredible support was indeed important in completing this thesis. I am grateful for the melodious Cantonese songs with beautiful lyrics that accompanied me during the days and nights of doing research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

A

AI Artificial Intelligence

AR Abnormal Return

AP Abnormal Performance

C

CS Computer Science

CSR Corporate social responsibility

COGS Cost of Goods Sold

D

DDEA Data-driven Event Analysis

E

ESE Emerging Sustainability Events

ER Expected Return

EP Expected Performance

ESG Environmental, Social, and Governance

G

GRI Global Reporting Initiative

L

LP Labor Productivity

N

NER Named Entity Recognition

NLP Natural Language Processing

O

OSCM Operations and Supply Chain Management

P

PR Public Relation

R

ROA Return on Assets

ROS Return on Sales

S

SR Sustainability Reporting

V

VUCA Volatile, Uncertain, Complex, and Ambiguous

1. CHAPTER 1: INTRODUCTION

1.1. BACKGROUND AND OVERVIEW

As an important part of the manufacturing and production business, the fashion industry is being urged to address sustainability issues by a wide range of stakeholders. A recent UN report states that the fashion industry accounts for nearly 10% of global carbon emissions and 20% of global wastewater (United Nations Economic Commission for Europe, 2018). As such, due to the resource- and energy-intensive nature of the fashion industry, fashion companies play a representative role among businesses facing sustainability issues.

Stakeholders rely on information released in public channels to understand companies' sustainability strategies and practices, such as company news and reports. According to signaling theory, due to the presence of private information, information asymmetry exists among different parties as they receive a different volume of information about firms' practices (Stiglitz, 2002). The release of additional information addressing the information asymmetry can trigger signaling effects, which reflect the reactions from the market and stakeholders (Connelly et al., 2011). In recent years, although governments have been considering establishing regulations to demand detailed sustainability information and on emission and resource consumption from firms' internal operations, it remains a challenge to govern such reporting (McKinsey, 2022), and firms are uncertain about the performance impacts of such disclosures. Therefore, the sustainability information available to stakeholders today is still limited, resulting in information asymmetry. Sustainability reporting enables companies to disclose sustainability information to signal to their stakeholders through voluntary disclosures that provide additional information about their sustainability performance beyond the mandatory disclosures. The sustainability information published can be important for addressing information asymmetries and can lead to signaling effects. Therefore, managers need to understand how sustainability reporting can affect the operations and performance of manufacturing companies. In the first study, we consider the “Effects of Sustainability Reporting on Firms’ Market and Operations Performance — Five Long-Term Event Studies.”

Beyond sustainability reports, there are many potential events that exist that may trigger a market reaction and affects firms’ operations. In order to gain insights into the relationship between an event and firm performance, the event study method is one of the most popular empirical research methods utilized in the literature. The event study method is grounded in the efficient market hypothesis, which is based on the premise that the value of market information will be reflected in the stock prices in the financial markets. To conduct an event study, event identification is the starting point of the research and this is a manual procedure. However, according to a recent literature review on short-term event studies (Ding et al., 2018), the existing event research methods are unable to handle large and complex event sets. Most event studies are hypothesis-driven, generally examining a single event in each paper. This can be time-consuming because event identification relies on manual event identification and data collection and fails to take into account more than one event at a time. There remain unsolved problems for both managers and researchers on how to advance the events recognition approach. Taking advantage of the latest developments in AI, such as in NLP, researchers are now able to study large unstructured data sets in novel ways. Therefore, with the aim to advance the event identification approach using AI, in Study 2, we develop the work "EventMining: Identifying Sustainability Event Cases Using Natural Language Processing."

In the process of conducting event studies, researchers generally use a matching strategy to build a different-in-differences setting for a quasi-natural experiment and then estimate the Abnormal Return (AR). However, empirical analysis of multiple and complex events is beyond the capacity of researchers as this still involves a manual process. Therefore, there is a need to extend the *EventMining* approach to identify events through automation of the event study analysis to enable a quantitative analysis of the performance effects of multiple events. As such, the proposed method can be employed for data-driven event studies to produce research responding to the call for data-driven Operations and Supply Chain Management (OSCM) research in the data science era[1]. Therefore, we conduct Study 3, "Managing the Unexpected — A Large-Scale Data-driven Event Analysis on Emerging Sustainability Events."

1.2. MOTIVATIONS FOR STUDYING SUSTAINABILITY EVENTS

From a theoretical perspective, there are several research gaps that have motivated this dissertation. First, the literature shows inconsistent results in considering the impact of sustainability reporting on firms' performance, which requires studies to be carried out based on long-horizon data. While GRI reporting has been found to improve corporate social performance, market value, and financial performance (Lee & Maxfield, 2015; Loh et al., 2017; Yang et al., 2021), some studies have revealed that its impact is not significant (Verbeeten et al., 2016) or that the effect is limited to specific industries

[1] https://connect.informs.org/msom/events/datadriven2020

and contexts (Bernard et al., 2015). Furthermore, most of the existing research employs short-horizon data (e.g., three years) for estimating the effects of sustainability reporting (Yang et al., 2021), which is also a possible cause for the inconsistent results. As such, Study 1 aimed to conduct event studies based on a long-horizon data set to evaluate the impact of sustainability reporting. The empirical evidence obtained has important implications for the research and practices of manufacturing firms to help them improve their operations management by developing sustainability reporting strategies.

Second, although the literature has shown SR can drive profitability (Yang et al., 2021) and market valuation (Schadewitz & Niskala, 2010), its effects on internal operations and employees are less understood (Fernandez-Feijoo et al., 2014; Sweeney & Coughlan, 2008). Apart from focusing on finance/market outcomes that are sensitive to external stakeholders, it may be overlooked how operational outcomes depend more on employees and sustainable operations. The question of whether reporting is a purely public relations exercise and activity for generating a market reaction or whether companies can benefit in their operations and production needs an answer. Thus, Study 1 also aimed to study the effects of sustainability reporting on firms' operational efficiency.

Third, there is generally an absence of *observability* in research examining the relationship between sustainability reporting and firms' performance. Prior research on GRI reporting has employed the *signal strength* (e.g., Yang et al., 2021) and *signal environment* (Bae et al., 2018; Ching & Gerab, 2017; Robinson et al., 2011) of signaling theory as the theoretical foundations for their empirical setting. However, few studies have examined the role of *observability* and estimated the related factors affecting the performance impacts of sustainability reporting. While SR signals to the stakeholders and can lead to market reactions, the observability of the signals may amplify or mitigate the influences. Also, apart from the factors that the firms cannot control, the knowledge of observability can provide managers with better solutions about how to manage their sustainability disclosures and stakeholder relationships. Therefore, another motivation of Study 1 was to gain an understanding of *whether* and *how observability* affects the performance impacts caused by sustainability reporting.

Fourth, the lack of advanced methodology for event identification limits the analytics capacity of researchers in the digital era. The event study method has been employed by researchers to investigate various topics, such as supply chain disruptions (Hendricks & Singhal, 1997; Zhao et al., 2013) and environmental management (Jacobs et al., 2010). The event study method provides a systematic way of exploring the performance impacts of events. Yet, to date, the methods for event recognition still rely on researchers' manual works. While there may be rich data available from various sources that can be used for strategy development and decision-making, the data can be complex and unstructured. Models utilizing data analytics and AI techniques can provide innovative solutions for addressing this problem. As such, Study 2 was motivated to develop an approach to improve the current event recognition method, by integrating machine learning and NLP models.

Lastly, although there is literature studying different sustaianbility events (Jacobs & Singhal, 2020; Lo et al., 2018; Xu et al., 2022) using the event study approach, there is a lack of understanding of Emerging Sustainability Events (ESEs). Unlike event studies that focus on a single event, the analysis of emerging events requires a comprehensive perspective and, therefore, multiple events to be analyzed. A gap in the literature has thus arisen from one main reason: the lack of analytical systems for automating event analysis. Data-driven analysis can be an innovative way to solve this problem, and programming can be a way to develop the system. Therefore, the motivation of Study 3 was to apply the approach presented in Study 2 and to extend it with data-driven analysis. To sum up, we identify the main research gaps that motivate this dissertation. This highlights the importance and timeliness of this dissertation to the literature and practice. Figure 1.1 presents the structure of this thesis.

1.3. STRUCTURE OF THIS THESIS

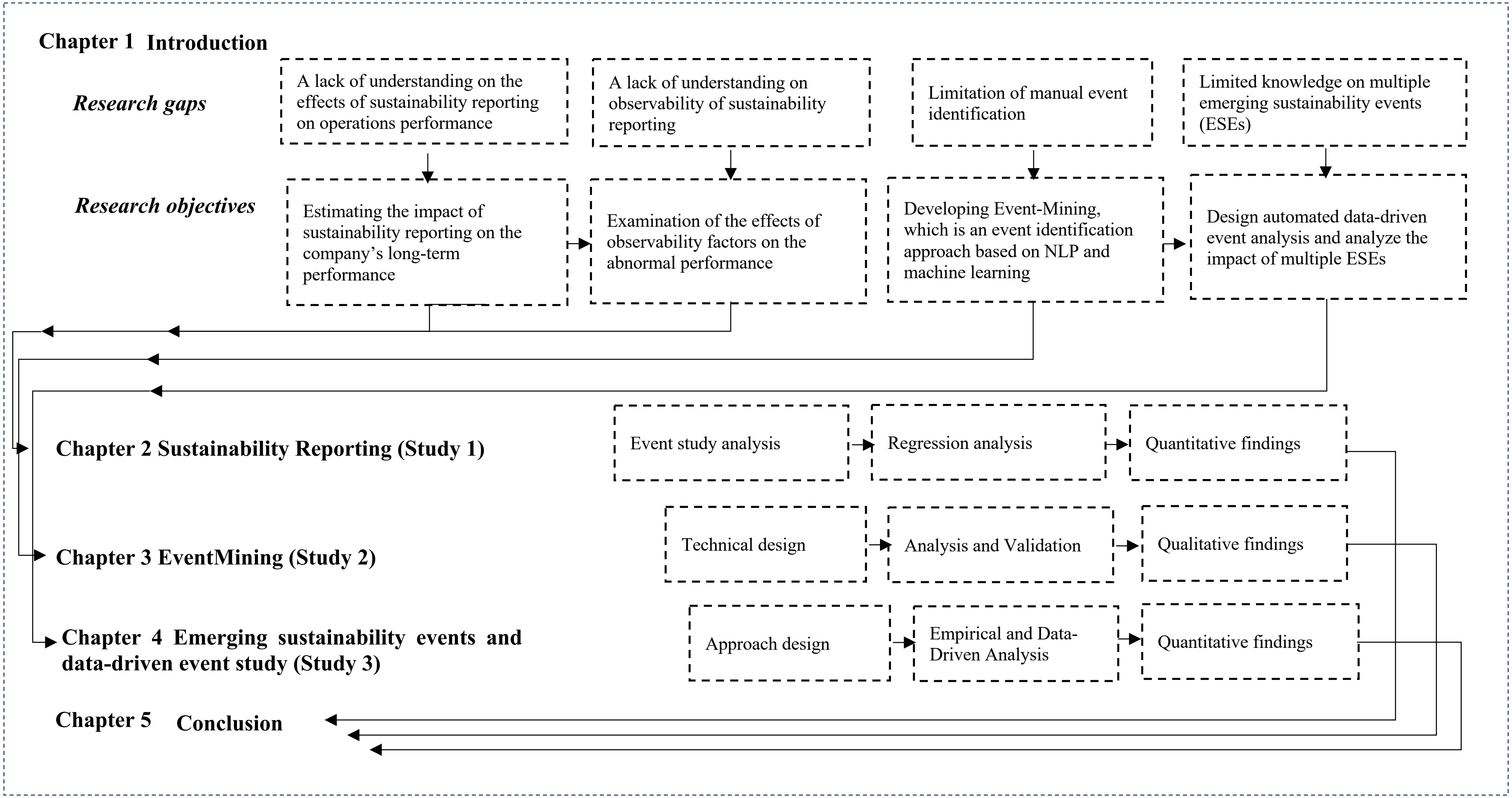


Figure 1.1 Structure of this thesis

2. CHAPTER 2: EFFECTS OF SUSTAINABILITY REPORTING ON FIRMS' MARKET AND OPERATIONS PERFORMANCE — FIVE LONG-TERM EVENT STUDIES

2.1. INTRODUCTION

Sustainability Reporting (SR) is a form of corporate social responsibility (CSR) communication. According to signaling theory (Spence, 2002), SR can signal underlying quality of a reporting firm to external stakeholders, e.g., investors, shareholders, customers, and government, by means of a *costly signaling effect* (Bird et al., 2005). A costly SR standard signals superiority. The signal that corporate governance is effective in guiding environmentally and socially responsible efforts (Bae et al., 2018) can drive investment. Reporting sustainability performance enhances legitimacy, credibility, and reputation, leading to positive market valuation (Schadewitz & Niskala, 2010) and profitability (e.g., Yang et al., 2021). SR is known to be an effective marketing communication, public relation (PR), and legitimacy tool to please external stakeholders (Sweeney & Coughlan, 2008). However, SR can inform external stakeholders sufficiently to pressure reporting firms (Fernandez-Feijoo et al., 2014; Sweeney & Coughlan, 2008). Investors want reporting firms to gain both market performance and operational efficiency by adopting stringent SR standards. As few standards such as ISO 9001/14001 and OHSAS 18001 are designed to develop production systems for improving operational efficiency (Lo et al., 2014), it is not clear whether any SR standard can drive *operational efficiency.*

This study extends the notion of *costly signaling* (Bird et al., 2005) to explain the broader effects of SR. Costly signaling means only capable firms can bear and absorb the high *signal costs* of meeting stringent SR. For example, Global Reporting Initiative

(GRI) is known for its quality and stringent reporting requirements. GRI is adopted by only 74 percent of the world's largest 250 firms and 51 percent of the firms listed on the S&P 500 (GRI, 2020). Evidence shows GRI reporting drives environmental, social, and governance (ESG) performance, but traditional CSR reporting fails to achieve such multiple benefits (Lee & Maxfield, 2015). While GRI signals *quality* (Cuadrado-Ballesteros et al., 2016) and *strength* (Yang et al., 2021) to external stakeholders, its broader effect on operational employees who collect and prepare data and produce operational outcomes that go into the reports remain unclear.

The use of stringent SR can affect operations both positively and negatively. A costly signal from a stringent SR adds operational costs through activities such as certification, preparation, audit, compliance, and producing the SR. To reduce risks of failing to meet SR standards, a firm may build up bureaucracies that offset operational efficiency (Li et al., 2022). Resources are diverted to less productive activities like monitoring or certification. This additional cost burden can reduce productivity. However, the preparation for SR reporting sends other signals to employees and suppliers, such as leadership, commitment (Robinson et al., 2011; Wiengarten et al., 2017; Yang et al., 2021), and awareness that drive motivation (Scott et al., 2022) and efforts to overcome the additional cost. To explain these effects, it is necessary to understand how external stakeholders' responses to SR signal internal stakeholders through a "reverse" signaling effect. Thus, we need to explicate interactions between external and internal stakeholders.

To understand the signaling processes when external and internal stakeholders interact, we integrate stakeholder theory (Verbeeten et al., 2016) with signaling theory and adopt the open systems perspective of Klassen (1993). Under stringent standards like GRI, senior managers and operational employees feel pressured by external stakeholders (Martínez-Ferrero & García-Sánchez, 2017), who expect sustainable operations to achieve ESG in a cost-efficient manner. Consumers expect positive integrity and capability signals (Mollenkopf et al., 2022). Through SR, senior managers signal to external stakeholders that they can compensate the cost of reporting by achieving operational cost savings (Klassen & McLaughlin, 1996). Through internal interactions, senior managers will clarify the sustainability roles of operational employees and targets for operational improvement. Such interactions drive the operational team to play a more strategic role in SR and use SR to improve operational efficiency.

Meaningful interactions between external and internal stakeholders occur when they can efficiently observe signals from each other. Signaling efficacy depends on *signal observability,* defined as "the extent to which outsiders are able to notice the signal" (Connelly et al., 2011, p. 45). Observability also matters to employees. Employees observe senior management's commitment, and they are aware of being observed by external stakeholders. Observability drives accountability, according to accountability theory (Lerner & Tetlock, 1994). The more firms talk about their sustainable operations, the more observability increases. To consider observability by both external and internal stakeholders, we use three proxies: *first-time reporting, reporting frequency,* and *media exposure.* In addition to boosting market optimism, *first-time reporting* can motivate employees. *Reporting frequency* can pressure senior managers and operational employees to improve sustainability performance and productivity.

Likewise, *media exposure* can send a positive, neutral, or critical message that affects both market responses and employees' morale.

To test the above conjectures, this study uses objective data from GRI reports among US manufacturing firms for the period from 1999 through 2020). There is no shortage of studies that show SR drives financial performance, e.g., Return on Assets (ROA), Return on Sales (ROS) (Bae et al., 2018; Ching et al., 2017), and market responses, e.g., share price, market valuation (Loh et al., 2017; Verbeeten et al., 2016). However, these are lagging or external indicators not actionable by operations managers. Finance/market performance also depends on cost and labor efficiency. Thus, this study considers two types of operational efficiency: *labor productivity* and *COGS/Sales*, in addition to market responses, e.g., *Tobin's q* and *market value*. We first use event studies to estimate the long-term effects of GRI reporting vs. non-reporting firms. We then use regressions to test the effects of *first-time reporting*, *reporting frequency,* and *media exposure*.

2.2. THEORETICAL BACKGROUND AND HYPOTHESES

2.2.1. Sustainability Reporting (SR) and Firm Performance

Previous studies on SR can be divided into three streams (Appendix I). One stream of research examines financial impacts (Chen et al., 2015), and reduction of pollution expenditure of GRI reports (Chiu et al., 2017). The second stream focuses on environmental impacts, e.g., emissions reduction (Bernard et al., 2015), CSR performance, market value (Lee & Maxfield, 2015), and profitability (Yang et al., 2021). The third stream examines the determinants of SR (Chen & Bouvain, 2009), such as stakeholder pressures (Fernandez-Feijoo et al., 2014), and enablers, e.g., legal system and enforcement mechanisms (Kolk & Perego, 2010). This study expands the first two streams of literature by integrating stakeholder theory and signaling theory into an integrated framework grounded on the assumptions below.

Internal stakeholders play a significant role in preparing for SR and achieving goals set out in the report. They assure the market that all risks associated with ESG are under control. They provide information about the sustainable operations of the reporting firm and its supply chain. For example, GRI requires details about how a firm manages sustainable procurement, materials, energy, water, effluents, biodiversity, emission, employees, and many other operational aspects in its supply chain (see www.globalreporting.org). GRI requires the collection and dissemination of sustainability information internally within a firm by operational employees through their daily operations. Operational employees will have a good understanding of the sustainability positions of the firm. They produce and signal sustainability information to the external stakeholders. Reporting using GRI means many operational tasks must be more transparent to their stakeholders. While this adds risks of the operation becoming more visible for scrutiny (Swift et al., 2019), it also exposes opportunities for efficiency gain (Wong et al., 2021).

Internal and external stakeholders interact through signaling. Internal performance goals are shaped by pressures from external stakeholders. External stakeholders expect efficiency alongside with positive finance/market outcomes of SR. Deviation from aspirational targets (set by GRI) can drive the use of actions of distrust (Wiengarten et al., 2019) and scrutiny by stakeholders. Moreover, *operational efficiency* can be compromised because GRI guidelines are very extensive, making it difficult for some firms to implement (Ferreira Quilice et al., 2018). SR activities are carried out by operational and sustainability employees, supported by senior managers who define goals. These goals are affected by interactions with external stakeholders. Thus, the operational outcomes of GRI reporting depend on both internal and external stakeholders and how they interact. Such interactions put demand on internal resources to capture, consolidate, measure, assess, and analyze data related to sustainable activities and performance. The interactions between employees and managers lead to learning that can improve operations. Thus, market and operational outcomes depend on interactions between internal and external stakeholders.

The *costly signaling effect* (Bird et al., 2005), due to signaling between external and internal stakeholders, can explain the broader effects of SR. Signals about sustainable activities and performance are produced by operational functions. External stakeholders expect firms adopting stringent SR to produce above-average sustainability performance, which requires a costly investment. As the most cited set of guidelines (Brown, de Jong, & Lessidrenska, 2009; Pérez-López et al., 2015; Toppinen & Korhonen-Kurki, 2013), GRI is a demanding SR standard (KPMG, 2017). Goel and Cragg (2005) argue that GRI is not a management tool. We disagree: GRI is a communication tool for CSR as well as an internal operational tool for driving internal improvement. GRI requires firms to provide comprehensive reporting on operations, procurement, and the supply chain. In addition, GRI produces sector-specific benchmarking (ranking) tables, which adds pressure to outperform rivals or meet higher industry standards without scarifying *operational efficiency*.

2.2.2. An Integrated Framework

This study proposes an integrated framework to reflect the interactions between internal and external stakeholders. In particular, signals from SR matter to both internal operations and external stakeholders. As shown by the framework in Figure 1, in an open system internal and external stakeholders interact (Klassen, 1993) and such interactions set goals and influence performance. We adapt the notion of market gains (as market response) and cost savings (as operational efficiency) from Klassen and McLaughlin (1996). *Market responses* depend on external interactions (with investors, shareholders, customers, etc.) that affect market valuation and market share (through sales growth). *Operational efficiency* is driven by external interactions that pressure internal stakeholders, e.g., operations, sustainability, and senior managers. Market responses and operational efficiency are influenced by *signal cost* and *observability*. Signal observability is amplified by *first-time reporting*, *reporting frequency*, and *media exposure*.

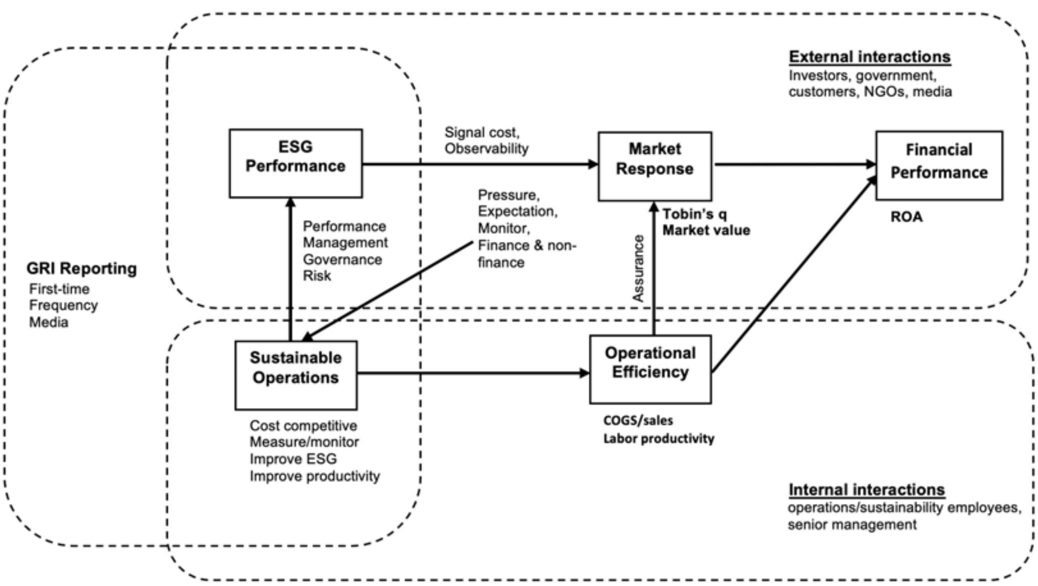


Figure 2.1 Conceptual framework

Figure 2.1 considers both *"forward"* and *"reverse" signaling* effects. For example, first-time reporting will trigger an expectation from the market to repeat reporting with better financial and non-financial performance. In addition to ROA and profits, investors want to be assured that the reporting firm can cope with the cost of the GRI reporting by gaining operational efficiency.

2.2.3. External and Internal Interactions

There are three key players in a signaling process: the signalers, receivers, and agents (Connelly et al., 2011). SR serves as a signal source that provides information to reduce information asymmetry between a signaler (reporting firm) and receivers (stakeholders) (Spence, 2002). In the internal interaction model, the managers and operational employees who produce SR are signalers – they set sustainability and operational performance targets and work to achieve them. In the meantime, employees are receivers of SR information as they produce and are exposed to the sustainability information. In the external interaction model, investors and customers are key stakeholders who produce market responses, which send reverse signals to the internal stakeholders.

By informing the prospects of organizational sustainability in the long run (Delmas & Montiel, 2008), SR helps external stakeholders generate a perception on firms' sustainability responsibility and, in turn, drives market optimism. Market-based performance, such as market valuation, helps firms to secure funds to invest in sustainability initiatives (Siegel, 2009). Investment is required to access resources and innovate. In addition, SR increases transparency in environmental and social impacts. It provides information about firms' sustainability policy, performance, and initiatives, and collaboration with strategic partners, governments, and capital markets. Strategic partners and governments care about firms' sustainability practices. Investors will invest only if operational risks are addressed. SR assures investors that various costs and risks are being mitigated.

GRI is an effective tool for the reporting firms to drive sustainability efforts, assess and protect reputation, and enhance brand value (Brown, de Jong, & Levy, 2009). As argued, the quality, strength, and costly signals of stringent SR like GRI influence investors to have a positive *market response* to the reporting firm. The costly signal argument suggests that GRI reporting firms have higher underlying quality and are therefore better positioned to drive positive market reactions than non-reporting firms. The market generally responds positively to the adoption of stringent standards that reflect the underlying quality and costly investment (Connelly et al., 2011). *Signal costs* can prevent poorer quality firms that cannot meet the rigorous standards from making baseless claims. It requires effort to audit sustainability practices to comply with SR. Since stringent standards such as GRI reporting provide information beyond mandatory disclosure, it requires investment and effort (Cantor et al., 2012; Feng et al., 2020). About half of the firms listed on the S&P 500 have not even adopted them (Governance & Accountability Institute, 2020). Only firms with underlying quality can meet the stringent requirements of such demanding reporting standards (e.g., Bae et al., 2018; Loh et al., 2017; Robinson et al., 2011; Yang et al., 2021).

SR is not just a public relations (PR) exercise unrelated to firms' operations. SR standards like GRI demand significant input and effort from operations functions. The costly signal effect can boost market responses only if the firm can prove that they can improve operational efficiency as a means of compensating the cost of GRI. GRI attracts attention and higher expectation from the market. It is important to acknowledge that the market also expects that committing to GRI does not reduce cost efficiency. As such, reporting to external stakeholders creates a *"reverse"* signaling process that drives senior managers to promise *operational efficiency*. This pressure drives *internal interactions* among managers, operational, and SR employees to set targets and initiatives to drive ESG and operational improvement. For example, driven by the *"reverse" signaling* effect of GRI, Walmart committed to a four-year plan in 2008 to improve the energy efficiency of the factories of its 200 major suppliers by 20 percent (BSR, 2010). Walmart strove to meet its target to avoid stakeholders finding contradicting information that suggests that the company failed to cope with the cost of GRI reporting.

To achieve the operational efficiency expected by the market, managers will have to provide more supports to the operational team. The theory of perceived organizational support explains that employees expect their employer to fulfill their sustainability responsibilities (Eisenberger et al., 1986). Firms can actively demonstrate efforts and commitment to increase employees' citizenship behaviors (Feng et al., 2020). Klassen and McLaughlin (1996) argue that investment in environmental management can drive higher morale and increase productivity. For non-reporting firms, employees are less motivated, as they receive limited information and expectations from their managers. This lack of communication results in information asymmetry between employees and managers, leading to unclear roles and responsibilities in sustainability. In contrast, employees involved in GRI conduct compliance activities and data collection, and information asymmetry between managers and employees is reduced. Employees can process the relevant information to form a better understanding of the firm's commitment. As such, employees are likely to gain affective commitment and intrinsic motivation (Cantor et al., 2012).

GRI reporting disciplines the reporting firm to design procedures for consistent assessment of sustainability performance and for taking appropriate actions to address negative societal and environmental impacts. A similar effect can be found in the adoption of ISO 9000 (Corbett et al., 2005). In doing so, firms identify and reengineer operations for internal quality and efficiency with the aim of reducing waste and resource consumption (Wong et al., 2012), consequently improving *operational efficiency* to compensate the cost of implementing GRI and improving the well-being of the community. SR also serves as a tool for monitoring purposes (Martínez-Ferrero & García-Sánchez, 2017) and identifying areas for operational improvement. For example, Walmart constructed its supplier sustainability assessment scorecard to signal its intentions to enhance energy efficiency and reduce carbon emissions (PureStrategies, 2021). Thus, we expect GRI reporting firms to gain more positive market response and operational efficiency than do non-reporting firms.

> *H1. Compared with non-reporting firms, firms that produce GRI reports achieve higher abnormal (a) market responses and (b) operational efficiency.*

2.2.4. The Effects of Observability

Past studies show that GRI reporting can improve CSR performance and *market value* (Lee & Maxfield, 2015; Loh et al., 2017), while others find insignificant effects (Verbeeten et al., 2016). In addition to SR reporting standards, similar signaling effects are achieved by announcing listings in indexes (e.g., Dow Jones Sustainability Indices) or the appointment of chief sustainability officers (e.g., Robinson et al., 2011; Wiengarten et al., 2017; Yang et al., 2021). These proxies reflect signal quality or strength but ignore signal efficacy, which reflects how well these signals are brought to the attention of receivers. *Signal observability* is the extent to which receivers notice and receive the signal (Connelly et al., 2011). An effective signal must be readily observed and processed. Observability is a crucial measure to understand interactions between internal and external stakeholders through the *"reverse" signaling* effect. Under the gaze and scrutiny of external stakeholders, reporting firms are forced to solve their sustainability problems rather than greenwashing them. More attention from external stakeholders also leads to an increase in cost (to respond to criticism), which can drive efforts to improve operational efficiency. We consider three proxies for observability: *first-time reporting*, *reporting frequency,* and *media exposure*.

First-time reporting increases observability in that a firm becomes a reporting firm. Non-reporting by firms causes high information asymmetry and a barrier to gaining legitimacy and trust from their external stakeholders. Producing SR that follows a costly standard (like GRI) that few can comply with the first time produces a costly signal and increases observability. When a firm releases its first-ever SR that applies reputable standards such as the GRI standards, this *costly signal* will certainly be noticed. For example, in 2005, Walmart released its first "Ethical Sourcing Report" and later measured and reported its results based on GRI in 2009. First-time reporting using GRI indicates a switch to strict reporting guidelines. The switch to GRI reporting by Walmart as the sector leader was consequential, as very few firms in the grocery sector had adopted the standard at that time. It sent a strong signal to internal and external stakeholders that the firm is committed to sustainability, and they have elected to adopt the standard because they have the capability to achieve operational efficiencies.

H2. First-time GRI reporting is associated with higher (a) market responses and (b) operational efficiency.

Observability is enhanced by repeatedly sending the same consistent messages (Connelly et al., 2011). *Reporting frequency* refers to the number of times that a signal is transmitted to receivers. Frequency of messages affects observability and abnormal performance (Janney & Folta, 2003). Increased signal frequency indicates that the reporting firm understands the depth of the sustainability concerns and is demonstrating a consistent commitment and engaging in efforts toward sustainability. Signal frequency helps receivers to observe an increase in the effort of the firm. Also, the same signal sent multiple times can enhance the congruity of the messages, and reduces any confusion (Gao et al., 2008). Repeating signals can reduce information asymmetry, perpetuate the signaling effects (Janney & Folta, 2006; Park & Mezias, 2005), and reinforce the same messages (Balboa & Martí, 2007). All these drive positive market responses. Reporting GRI over the years also signals long-term and consistent commitment. Pressured by the "reverse" signaling effect, reporting firms feel the need to demonstrate improvement in subsequent reporting, including gains in operational efficiency.

H3. Frequent GRI reporting is associated with higher (a) market responses and (b) operational efficiency.

Signal observability is amplified by signaling agents, e.g., media. *Media exposure* is defined as "the aggregated news reports relating to a specific company within a prescribed period" (Wartick, 1992, p. 34). Firms may announce sustainability targets and achievements in mass media to reach large audiences. The media can then transmit signals (i.e., sustainability information) to the public. Although media exposure is not entirely controlled by the reporting firms, they may organize press releases to publicize and increase exposure. Stakeholders may use media to understand the reporting firm. As a "broadcaster," the media's accounts of GRI reports can increase the frequency of a message and increase its breadth, allowing stakeholders to synthesize it to form an understanding and verification of the information from various sources. Media may critique firms based on their own opinions and analyses, which provides additional sources of information for external stakeholders to verify the information they have received. Media drives positive market responses when the information from different sources is consistent (Connelly et al., 2011; Gao et al., 2008). Media can stir market responses in many ways through positive or negative news. For example, the initial attempt of Walmart to use GRI guidelines was criticized by some media. Stakeholders could then use the negative messages to scrutinize the firm and pressure them to put in more effort and address their concerns. Walmart responded to media criticism by improving its operational efficiency.

H4. Media exposure of GRI reports is associated with higher (a) market responses and (b) operational efficiency.

2.3. RESEARCH METHOD

2.3.1. Data Sources

This study relies on three data sources: GRI reporting, Compustat, and Factiva. We selected US manufacturing firms (SIC codes 20 to 39) that produced SR based on GRI standards from 1999 to 2020 because they (1) account for a large proportion of the firms that produce SR; (2) face a clear set of environmental and social regulations; (3) consume significant energy and produce pollution and waste; and (4) receive more attention from stakeholders.

Table 2.1 Summary statistics of sample

Group No.	Sector Description	SIC code	Number of observations
1	Food, textiles, furniture, paper and chemicals	2000-2999	613
2	Rubber, leather, stone, metals, machinery, and equipment	3000-3569, 3580-3659, and 3800-3999	345
3	Computers, electronics, communications, and defense	3570-3579, 3660-3699, and 3760-3789	129
4	Automobile, aircraft, and transportation	3700-3759, and 3790-3799	85
5	Other		82
	Total		1254

Table 2.1 summarizes the sectors, SIC codes, and number of sample firms. We collected finance/market and operational efficiency data from the Compustat database (Corbett et al., 2005; Lo et al., 2014). Data for the last two years (i.e., 2021, 2022) were omitted to address the concern of missing data for our event study. To measure sustainability-related *media exposure*, we collected information from the Factiva database. Data are symmetrically capped at the 1% level in each tail to exclude outliers (Arora et al., 2020; Barber & Lyon, 1996). Table 2 shows the data filtering procedure and sample size.

Table 2.2 Data filter procedure and sample size

Dataset	Analysis	Sample size (observations)				
		ROA	LP	C/S	MV	TQ
Dataset A. Filtered GRI vs non- GRI reporting firms (sample without overlapping event windows)	Even study	278	275	276	266	274
Dataset B. Unfiltered data	Regression	1032	1002	1044	922	1036

Note: the whole sample = 1254 observations (263 US manufacturing firms with available GRI data); ROA = return on asset; LP = *labor productivity*; C/S = COGS/*Sales*; MV = *market value*; TQ = *Tobin's q*.

2.3.2. Event Studies

To test H1, we conducted five event studies to estimate the abnormal performance between firms in the sample (i.e., GRI reporting firms) and control group (i.e., non-GRI reporting firms). We adopted a four-year event window to measure abnormal performance of the five dependent variables, following the existing literature on sustainability events (Wiengarten et al., 2017). Specifically, the year of the event (i.e., the release of the SR) is defined as the event year (Year 0). Year -1 is defined as the base year. The first and second years after the event year are defined as Year 1 and Year 2, respectively.

We matched a control portfolio for each sample observation based on each dependent variable in the base year (i.e., Year -1). Consistent with existing literature (e.g., Arora et al., 2020; Barber & Lyon, 1996; Hendricks et al., 2015; Lo et al., 2014; Xia, Singhal, & Zhang, 2016), we adopted a multiple-step approach with progressively relaxed rules to avoid loss of any of the sample firms (Hendricks et al., 2015). First, we identified the control group, which has the same two-digit SIC and a dependent variable value within 90% to 110% of the sample firms. Second, if there were unmatched firms, we relaxed the rules to match firms with a one-digit SIC code and the dependent variable value within 90% to 110% of those of the sample firms, respectively. Third, if there were unmatched firms in the first two steps, we relaxed the rule to match control firms by the dependent variable value within 90% to 110% of that of the sample firms only. Last, if there were unmatched firms in the last three steps, we selected the matching firm with the closest performance without the rule for including the dependent variable and SIC code. We also set a rule of a factor of 50% of the total assets to control the firm size of the control group in the matching steps (Hendricks et al., 2015). On average, each sample firm matched with 12.16 (ROA), 7.46 (*labor productivity*), 21.05 (*COGS/Sales*), 14.70 (*Tobin's q*), and 5.37 (*market value*) control firms.

The formulas for calculating the abnormal performance (AP) are shown as follows:

$$AP_{(t+i,t+j,p)} = PS_{(t+j,p)} - EP_{(t+j,p)} \quad (2.1)$$

$$EP_{(t+j,p)} = PS_{(t+i,p)} + \frac{1}{m_q}\sum_{q=1}^{m_q}\left(PC_{q,t+j} - PC_{q,t+i}\right) \quad (2.2)$$

where *AP* is the abnormal performance; *EP* is the expected performance; *PS* is the performance of the sample firms; *PC* is the average performance of the firms in the control group; *t* is the base year (i.e., year -1); *i* is the start year for comparison (i.e., -1, 0, 1); *j* is the end year for comparison (i.e., 0, 1, 2); *p* is the index of firms in the sample group (e.g., 1, 2, …); *q* is the index of firms in the control group (e.g., 1, 2, …); *n* is the number of firms in the sample group; and m_q is the number of firms in the control group of index *q*.

To avoid event windows overlapping, we restricted the events without overlapping in the estimated windows (i.e., 4-year). In other words, the first-time event and later events without overlapping are included (MacKinlay, 1997). Because of the availability of variables, the sample is consistent, but there should be a variance among sample size for different dependent variables (Lo et al., 2014). As a result, the sample sizes for the dependent variables ROA, *labor productivity*, *COGS/Sales*, *market value*, and *Tobin's q* are 278, 275, 276, 266, and 274, respectively (see filtered Dataset A in Table 2).

3.3 Variables

Dependent variable. We measured two types of operational efficiency. *Labor productivity* is defined as net operating income divided by the number of employees (Fan et al., 2018). *COGS/Sales ratio* is measured by the bottom-line improvements in *Cost of Goods Sold (COGS)*, including direct labor and materials costs, divided by *Sales* (Corbett et al., 2005). For market responses, we considered market valuation in terms of share *market value,* i.e., as the value of firms in the stock market, which is equal to market capitalization. We also included *Tobin's q,* a market measure of firm values that is forward-looking and risk-adjusted (Montgomery & Wernerfelt, 1988). *Tobin's q* is a financial market-based measure. Defined as the capital *market value* of a firm divided by the replacement value of its assets, *Tobin's q* incorporates a market measure of firm value. The above measures of operational efficiency and market responses affect the overall profitability of the firm. We consider this an additional dependent variable, *ROA,* defined as net operating income (before depreciation, interest, and taxes) divided by total assets (Lo et al., 2018).

Independent variables. A natural logarithm of the number of media reports related to the sample firms was used to measure the *media exposure* related to sustainability topics (Eftekhar et al., 2017). Information from the Factiva database was analyzed in the following steps. First, we searched business news in English related to the sample firms based on a keyword list[2] in the event year. Second, we measured the total number of news articles about each sample firm in the event year (Year 0). Finally, we calculated the natural logarithms of the ratio of the number of sustainability-related news of the sample firms in the event year to the number of total news articles in the same year. Following previous studies (Eftekhar et al., 2017; Liu et al., 2014), we did not categorize media reports as positive or negative. Based on this setting, we controlled for the interference of the variation in the trend of the number of news articles in different years.

First-time reporting is an indicator variable that takes a value of 1 if a firm conducts SR for the first time, and 0 otherwise, following the design of existing studies in the literature, to identify the first event (Xia, Singhal, & Zhang, 2016). This variable indicates the first report conducted by a firm, differentiating the disclosure behavior of its subsequent sustainability reporting. In the past, *reporting frequency* has been hard to measure due to a lack of data (Qiu & Kahn, 2018). *Reporting frequency* is defined as the consistency of firms in producing GRI reports after their first GRI reporting. It is measured as the number of reports produced by the firm divided by the difference between the end year of the event and the year of first reporting, as follows:

$$ReportingFrequency_{it} = \begin{cases} 0, & YearEvent_{it} = FirstEvent_i \\ \frac{NumberOfEvents_{it}}{YearEvent_{it} - FirstEvent_i}, & YearEvent_{it} \neq FirstEvent_i \end{cases} \quad (2.3)$$

where *i* is the index of the firm and *t* is the time index.

[2] Following the setting of existing literature (e.g., Arora et al., 2020), we used a keyword list to iteratively retrieve sustainability-related news from Factiva, including “environmental” or “environment” or “environmental disclosure” or “social responsibility” or “global reporting institute” or “GRI” or “corporate social responsibility” or “CSR reporting”, or “sustainability” or “sustainable” or “sustainability performance” or “environmental reporting.”

2.3.3. Regression Models

We use regression models to examine the effects of observability (H2 – H4). As shown below in Model, the dependent variable is regressed against sustainability-related media exposure, reporting frequency and first-time reporting. The control variables (i.e., Industry and Sample's ROA, and Firm Size) and dummy variables of year and industry fixed effects are included. We adopted OLS with a setting of industry and year fixed effects, and robust error. Additionally, we also conducted robust linear regressions (RLM) for a robustness check (Longoni et al., 2019). Appendix II shows the descriptive statistics and correlation matrices for all variables.

Model of Abnormal Performance (AP)

$$\begin{aligned} AP_{(i,j,p)} = \gamma_{10} &+ \gamma_{11}(industry\_dummy_{i,p}) + \gamma_{12}\,(year\_dummy_{i,p}) \\ &+ \gamma_{13}(ROA\_control_{i,p}) \\ &+ \gamma_{14}(industry\_adjusted\_ROA\_control_{i,p}) \\ &+ \gamma_{15}(media\_exposure_{p,i}) + \gamma_{16}(firm\_size_{i,p}) \\ &+ \gamma_{17}(first\_time\_reporting_{i,p}) + \gamma_{18}(reporting\_frequency_{i,p}) \\ &+ \mathrm{e} \end{aligned} \tag{2.4}$$

where i is the start year for comparison (i.e., -1, 0, 1); j is the end year for comparison (i.e., 0, 1, 2); and $p = 1, 2, \ldots, n$ is the index of the firms in the sample group.

2.4. RESULTS

2.4.1. Event Study Results

We use event studies to test out the time-lag effects of GRI reporting relative to non-GRI reporting firms. Consistent with previous studies, we adopted Wilcoxon signed-rank (WSR), binomial sign (Sign), and paired t-tests to examine the differences in the performance between the sample and matched control group based on the median and mean of the sample firms (Corbett et al., 2005; Fan et al., 2018; Hendricks et al., 2015; Lo et al., 2014; Zhang & Xia, 2013). Tables 2.3 and 2.4 show the results of the three tests. Following a prior study (Swift et al., 2019), we consider the sign test (instead of the WSR test) as more appropriate when the data are skewed (absolute skewness greater than 1) (Cowan, 1992). When the statistical results are not consistent, we use the skewness to choose the main results.

Table 2.3 Abnormal Performance Return on Assets (ROA), Labor Productivity (LP) and COGS/Sales (C/S)

Period	Var.	N	Median	Z[a]	Mean	*t*	% Positive	Z[b]
Year -1 to Year 0	ROA	278	0.006	3.059 (0.002) **	0.006	2.692 (0.008) **	59.35	3.275 (0.001) **
	LP	275	2.346	2.192 (0.028) *	2.025	1.621 (0.106)	56.00	1.930 (0.054) +
	C/S	276	-0.003	-2.140 (0.032) *	-0.017	-2.537 (0.012) *	46.01	-1.264 (0.206)
Year -1 to Year 1	ROA	254	0.013	3.576 (0.000) ***	0.012	3.930 (0.000) ***	61.42	4.019 (0.000) ***
	LP	252	5.146	3.011 (0.003) **	6.782	2.297 (0.023) *	59.12	2.835 (0.005) **
	C/S	255	-0.006	-3.367 (0.001) **	-0.031	-3.223 (0.001) **	43.52	-2.004 (0.045) *
Year -1 to Year 2	ROA	236	0.142	2.018 (0.044) *	0.008	3.801 (0.000) ***	56.78	3.284 (0.001) **
	LP	252	3.230	1.925 (0.054) +	5.643	2.433 (0.016) *	57.76	2.298 (0.022) *
	C/S	240	-0.003	-3.190 (0.001) **	-0.047	-3.654 (0.000) ***	46.25	-1.097 (0.272)
Year 0 to Year 1	ROA	254	0.007	2.447 (0.014) *	0.003	2.784 (0.06) *	57.87	2.738 (0.006) **
	LP	232	3.181	1.819 (0.069) +	6.457	2.160 (0.032) *	58.33	2.583 (0.010) *
	C/S	255	-0.003	-3.127 (0.002) **	-0.015	-2.888 (0.004)**	43.14	-2.129 (0.033) **
Year 0 to Year 2	ROA	236	0.009	1.627 (0.104)	0.006	2.529 (0.012) *	55.51	2.287 (0.022) *
	LP	232	2.463	1.819 (0.069) +	5.893	-2.096 (0.037) *	54.31	1.247 (0.212)
	C/S	240	-0.006	-2.812 (0.005) **	-0.031	-2.560 (0.011) *	41.67	-2.517 (0.012) *
Year 1 to Year 2	ROA	236	0.001	0.976 (0.329)	0.001	0.471 (0.638)	53.39	0.692 (0.489)
	LP	232	-0.174	0.680 (0.490)	0.360	-1.511 (0.132)	49.57	0.066 (0.948)
	C/S	240	-0.001	-1.213 (0.225)	-0.015	-1.433 (0.153)	49.17	-0.194 (0.846)

Note: † p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001 (2-tailed). P-value in parentheses. [a]Z-statistics for medians using Wilcoxon signed-rank tests. [b]Z-statistics for % positive using binomial sign tests. Event Year 0 is the year of the sustainability report release. Results based filtered dataset A.

Overall, the results show GRI reporting firms gain abnormal operational efficiency compared to non-reporting firms for one to three years, supporting H1(a) and H1(b). Table 2.3 indicates a significant change in the ROA between Year -1 and Year 0 (median change = 0.006, $p_{WSR} < 0.01$, $p_{sign} < 0.01$; mean change = 0.006, $p_{t\text{-}test} < 0.01$). This change continues in the period of Year -1 through Year 1 (median change = 0.013, $p_{WSR} < 0.001$, $p_{sign} < 0.001$; mean change = 0.012, $p_{t\text{-}test} < 0.01$), and Year -1 through Year 2 (median change = 0.142, $p_{WSR} < 0.05$, $p_{sign} < 0.001$; mean change = 0.008, and $p_{t\text{-}test} < 0.001$).

Table 2.3 also shows the results for *labor productivity* (row LP) and *COGS*/*Sales* (row C/S). During the period of Years -1 to 0, a marginal median change in abnormal *labor productivity* can be observed (median change = 2.346, $p_{WSR} < 0.05$, $p_{sign} < 0.1$; mean change = 2.025, $p_{t\text{-}test} = 0.106$). The trend continues during the period of Year -1 through Year 1 (median change = 5.146, $p_{WSR} < 0.01$, $p_{sign} < 0.01$; mean change = 6.782, and $p_{t\text{-}test} < 0.05$). Furthermore, the results show significant abnormal *labor productivity* from Year -1 through Year 2 (median change = 3.230, $p_{WSR} < 0.1$, $p_{sign} < 0.05$; mean change = 5.643, and $p_{t\text{-}test} < 0.05$).

Regarding *COGS*/*Sales*, the results indicate that there is a marginal median change during the period of Year -1 through year 0 (median change = -0.003, $p_{WSR} < 0.05$, $p_{sign} > 0.1$, skewness > 1; mean change = -0.017, $p_{t\text{-}test} < 0.05$). A more significant result was found during the period of Year -1 through Year 1 (median change = -0.006, $p_{WSR} <0.01$, $p_{sign} <0.05$; mean change = -0.031, $p_{t\text{-}test} < 0.01$). The results indicate a significant abnormal *COGS/Sales* during the period of Year -1 to Year 2 (median change = -0.003, $p_{WSR} < 0.01$, skewness > 1, mean change = -0.047, $p_{t\text{-}test} <0.001$). In the period of Year 1 through Year 2, the effect weakens (median change = -0.001, $p_{WSR} > 0.1$, $p_{sign} > 0.1$; mean change = -0.015, $p_{t\text{-}test} > 0.1$).

Table 2.4 shows the results of abnormal *market value* (row MV). During Year -1 through Year 1, positive and significant median change can be observed (median change = 329.969, $p_{WSR} < 0.05$, $p_{sign} = 0.109$, skewness < 1; mean change = 684.289, and $p_{t\text{-}test} < 0.05$). Likewise, in the period of Years -1 through Year 0, a marginal mean change is observed (median change = 4.469, $p_{WSR} > 0.1$, $p_{sign} > 0.1$; mean change = 458.171, $p_{t\text{-}test} = 0.106$). Significant median and mean changes are found over the period from Year 0 through Year 1 (median change = 142.752, $p_{WSR} < 0.1$, $p_{sign} < 0.05$, skewness > 1; mean change = 201.070, and $p_{t\text{-}test} < 0.05$) and from Year -1 through Year 2 (median change = 363.326, $p_{WSR} < 0.05$, $p_{sign} > 0.1$, skewness < 1; mean change = 1116.701, and $p_{t\text{-}test} < 0.05$).

Table 2.4 Abnormal Market Value (MV) and Tobin's q (TQ)

Period	Var.	N	Median	Z^a	Mean	t	% Positive	Z^b
Year -1 to Year 0	MV	266	4.469	0.783 (0.434)	458.171	1.621 (0.106)	50.00	0.000 (1.000)
	TQ	274	0.334	1.982 (0.047) *	0.442	1.947 (0.053) +	56.57	2.114 (0.034) *
Year -1 to Year 1	MV	254	329.969	2.396 (0.017) *	684.289	2.297 (0.023) *	55.33	1.600 (0.109)
	TQ	253	-0.103	0.763 (0.445)	0.520	1.434 (0.153)	47.83	-0.629 (0.530)
Year -1 to Year 2	MV	221	363.326	2.046 (0.041) *	1116.701	2.433 (0.016) *	53.85	1.076 (0.282)
	TQ	236	0.001	-0.270 (0.787)	0.279	0.633 (0.527)	50.42	-0.065 (0.948)

Year 0 to Year 1	MV	244	142.752	1.854 (0.064) +	201.070	2.160 (0.032) *	56.56	1.985 (0.047) *
	TQ	253	0.207	0.797 (0.426)	0.171	0.621 (0.535)	55.73	1.760 (0.078) +
Year 0 to Year 2	MV	221	64.304	1.441 (0.150)	739.807	2.096 (0.037) *	52.94	0.807 (0.420)
	TQ	236	-0.012	-0.200 (0.841)	-0.012	-0.303 (0.762)	50.00	0.000 (1.000)
Year 1 to Year 2	MV	221	11.054	0.163 (0.870)	723.476	1.511 (0.132)	50.23	0.000 (1.000)
	TQ	236	-0.028	-0.056 (0.955)	-0.028	-0.874 (0.383)	50.88	-0.195 (0.845)

Note: † p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001 (2-tailed). P-value in parentheses. [a]Z-statistics for medians using Wilcoxon signed-rank tests. [b]Z-statistics for % positive using binomial sign tests. Event Year 0 is the year of the sustainability report release. Results based filtered dataset A.

Table 2.4 also presents the results of abnormal *Tobin's q*. The results indicate that there is a significant median change during the period of Year -1 through Year 0 (median change = 0.334, $p_{WSR} < 0.05$, $p_{sign} < 0.05$, mean change = 0.442, $p_{t\text{-}test} < 0.1$). The trend did not persist during the period of Year -1 through Year 1 (median change = -0.103, $p_{WSR} > 0.1$, $p_{sign} > 0.1$, mean change = 0.520, $p_{t\text{-}test} > 0.1$), suggesting there is a short-term effect.

2.4.2. Regression Analysis

We use industry and year fixed effect models (Lo et al., 2018). We correct the selection bias endogeneity using the Heckman two-stage model (Arora et al., 2020). We adopted OLS with a setting of industry and year fixed effects, and robust error; RLM is also used to enhance robustness (Longoni et al., 2019). Tables 2.5, 2.6, and 2.7 summarize the results of four models of regression analyses: Model 1 the null model (control variables included), Model 2 OLS results, Model 3 RLM results, and Model 4 Heckman two-stage model for addressing sample self-selection endogeneity.

Panel A of Table 2.5 shows the regression results of abnormal *labor productivity*. The coefficient of first-time reporting is positive and significant ($\gamma\_OLS = 24.60$, $p < 0.01$, $\gamma\_RLM = 18.28$, $p < 0.001$). The coefficient of reporting frequency is positive and significant ($\gamma\_OLS = 29.42$, $p < 0.01$, $\gamma\_RLM = 18.28$, $p < 0.001$). Instead, the findings show insignificant effect of sustainability-related media exposure ($\gamma\_OLS = -1.234$, $p > 0.1$, $\gamma\_RLM = 1.309$, $p > 0.1$).

Panel B of Table 2.5 shows results for *COGS*/*Sales*. There is no significant effect of first-time reporting ($\gamma\_OLS = -0.009$, $p > 0.1$, $\gamma\_RLM = -0.012$, $p > 0.1$), reporting frequency ($\gamma\_OLS = 0.005$, $p > 0.1$, $\gamma\_RLM = -0.013$, $p > 0.1$), and media exposure ($\gamma\_OLS = -0.011$, $p > 0.1$, $\gamma\_RLM = 0.003$, $p > 0.1$) on *COGS*/*Sales*.

Table 2.5 Regression results of operational efficacy

	Panel A Dependent variable: *Labor Productivity*					Panel B Dependent variable: COGS/*Sales*				
	Model 1a Baseline (OLS)	**Model 1b OLS**	**Model 1c RLM**	**Model 1d (OLS with IMR)**	**Model 1e (RLM with IMR)**	**Baseline Model (OLS)**	**Model 2a OLS**	**Model 2b RLM**	**Model 2d (OLS with IMR)**	**Model 2e (RLM with IMR)**
Sample's Performance	13.27	10.73	38.56**	23.44	39.00**	0.156**	0.153**	0.0140	0.153**	0.0142
	(0.45)	(0.37)	(2.58)	(0.81)	(2.59)	(2.92)	(2.93)	(0.80)	(2.94)	(0.81)
Industry's Performance	-0.0924	-0.0889	-0.148+	0.196	-0.132	0.0939	0.0782	-0.00356	0.101	-0.00616
	(-0.76)	(-0.74)	(-1.75)	(1.33)	(-1.44)	(0.84)	(0.70)	(-0.03)	(0.78)	(-0.05)
Firm size	0.613	0.338	2.557**	-27.16***	1.034	0.0172*	0.0152*	0.00417***	0.0436*	0.00911*
	(0.38)	(0.21)	(2.63)	(-3.42)	(0.28)	(2.38)	(2.09)	(3.32)	(2.24)	(1.98)
Media Exposure (Sustainability Related)		-1.234	1.309	1.030	1.415		-0.0109	0.00331	-0.0129	0.00276
		(-0.35)	(0.56)	(0.30)	(0.60)		(-0.94)	(1.02)	(-1.07)	(0.85)
First-time Reporting		24.60**	18.28***	22.50*	18.19***		-0.00928	-0.0124	-0.00678	-0.0123
		(2.59)	(3.40)	(2.38)	(3.37)		(-0.46)	(-1.63)	(-0.33)	(-1.61)
Reporting Frequency		29.42**	22.40***	26.79**	22.32***		0.00497	-0.0131	0.00776	-0.0129
		(2.86)	(3.88)	(2.62)	(3.85)		(0.22)	(-1.61)	(0.35)	(-1.58)
IMR				-140.8***	-7.463				0.148+	0.0250
				(-3.72)	(-0.41)				(1.79)	(1.09)
Constant	19.62	-4.203	-15.06	432.5***	8.491	-0.160*	-0.153+	-0.0186	-0.610*	-0.0971
	(0.84)	(-0.15)	(-0.64)	(3.54)	(0.14)	(-2.14)	(-1.81)	(-0.55)	(-2.03)	(-1.24)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1041	1041	1040	1041	1041	1044	1044	1044	1043	1042
R^2	0.119	0.126	0.520	0.144	0.519	0.285	0.287	0.703	0.290	0.701
adj. R^2	0.035	0.041	0.473	0.059	0.471	0.219	0.218	0.674	0.220	0.672
F	1.422***	1.475***	11.14***	1.696***	10.87***	4.278	4.160***	24.42***	4.168***	24.21***

Note: *t* statistics in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed).

Table 2.6 Regression result for abnormal market value and Tobin's q

	Panel A Dependent Variable: *Market Value*					Panel B Dependent Variable: Tobin's q				
	Baseline Model (OLS)	**Model 1 OLS**	**Model 2 RLM**	**Model 3 (OLS with IMR)**	**Model 4 (RLM with IMR)**	**Baseline Model (OLS)**	**Model 1 OLS**	**Model 2 RLM**	**Model 3 (OLS with IMR)**	**Model 4 (RLM with IMR)**
Sample's Performance	-8009.8	-8108.4	-6884.7	-8459.5	-7002.4^{+}	-0.449^{+}	-0.424	-0.211	-0.425	-0.189
	(-1.17)	(-1.17)	(-1.64)	(-1.22)	(-1.68)	(-1.67)	(-1.56)	(-0.87)	(-1.60)	(-0.79)
Industry's Performance	-33721.3^{**}	-33689.9^{**}	-32732.7	-38558.7^{***}	-36766.2	-1.528	-1.325	-1.051	-1.129	-0.614
	(-2.99)	(-2.89)	(-1.26)	(-3.46)	(-1.43)	(-1.02)	(-0.87)	(-0.68)	(-0.66)	(-0.40)
Firm size	-1107.8^{+}	-1155.4^{+}	397.3	-7310.3^{***}	-3391.5^{**}	0.0341^{+}	0.0408^{*}	0.0305^{+}	0.294^{***}	0.279^{***}
	(-1.80)	(-1.74)	(1.33)	(-3.32)	(-3.12)	(1.77)	(2.06)	(1.81)	(4.18)	(4.55)
Media Exposure (Sustainability Related)		-634.4	414.8	-167.1	579.1		0.0460	0.0596	0.0278	0.0415
		(-0.51)	(0.54)	(-0.14)	(0.76)		(0.96)	(1.37)	(0.58)	(0.95)
First-time Reporting		972.2	2229.3	241.3	1702.8		0.226^{*}	0.314^{**}	0.247^{*}	0.333^{**}
		(0.34)	(1.23)	(0.08)	(0.94)		(2.30)	(3.05)	(2.49)	(3.25)
Reporting Frequency		1073.0	1815.7	89.71	1060.6		0.226^{*}	0.325^{**}	0.255^{*}	0.342^{**}
		(0.33)	(0.93)	(0.03)	(0.55)		(2.14)	(2.96)	(2.40)	(3.13)
IMR				-31920.5^{**}	-19013.5^{***}				1.316^{***}	1.273^{***}
				(-3.16)	(-3.51)				(3.88)	(4.15)
Constant	6401.2	4293.4	-18404.5^{*}	103455.9^{*}	41408.1^{*}	-0.477	-0.682	-0.646	-4.751^{***}	-4.606^{***}
	(0.27)	(0.18)	(-2.34)	(2.56)	(2.23)	(-1.06)	(-1.42)	(-1.40)	(-4.00)	(-4.38)
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	977	977	971	977	974	1068	1068	1066	1068	1067
R^2	0.110	0.110	0.241	0.119	0.269	0.171	0.176	0.185	0.191	0.199
adj. R^2	0.020	0.017	0.167	0.026	0.194	0.096	0.098	0.109	0.113	0.123
F	1.226	1.185	3.258^{***}	1.281	3.606^{***}	2.268^{***}	2.262^{***}	2.454^{***}	2.468^{***}	2.623^{***}

Note: t statistics in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed)

Panel A of Table 2.6 shows no significant effect of first-time reporting (*γ_OLS* = 972.2, *p* > 0.1, *γ_RLM* = 2229.3, *p* > 0.1), reporting frequency (*γ_OLS* = 1073.0, *p* > 0.1, *γ_RLM* = 1815.7, *p* > 0.1), and media exposure (*γ_OLS* = -634.4, *p* > 0.1, *γ_RLM* = 414.8, *p* > 0.1) on *market value*.

Panel B of Table 2.6 shows *media exposure* is insignificant in affecting *Tobin's q* (*γ_OLS* = 0.0460, *p > 0.1*; *γ_RLM* = 0.0596, *p > 0.1*). Instead, *first-time reporting* positively influences *Tobin's q* (*γ_OLS* = 0.226, *p* < 0.05, *γ_RLM* = 1.314, *p* < 0.01) and *reporting frequency* also has a positive and significant effect on *Tobin's q* (*γ_OLS* = 0.226, *p* < 0.05, *γ_RLM* = 0.325, *p* < 0.01).

Table 2.7 shows first-time GRI reporting has a positive and significant impact on *ROA* (*γ_OLS* = 0.0237, *p* < 0.01; *γ_RLM* = 0.0283, *p* < 0.01), as do reporting frequency (*γ_OLS* = 0.0237, *p* < 0.01; *γ_RLM* = 0.0278, *p* < 0.01) and sustainability-related media exposure (*γ_OLS* = 0.008, *p* < 0.01, *γ_RLM* = 0.008, *p* < 0.01).

Table 2.7 Regression results of profitability

	Dependent variable: ROA				
	Baseline Model (OLS)	**Model 1 OLS**	**Model 2 RLM**	**Model 3 (OLS with IMR)**	**Model 4 (RLM with IMR)**
Sample's Performance	0.0829^{***}	0.0840^{***}	0.116^{***}	0.0736^{**}	0.102^{***}
	(3.34)	(3.35)	(5.27)	(3.01)	(4.65)
Industry's Performance	8.08e-08	-1.92e-09	0.00000256	-0.000239^{+}	-0.000227^{+}
	(0.00)	(-0.00)	(0.02)	(-1.91)	(-1.76)
Firm size	-0.00372^{**}	-0.00295^{*}	-0.00318^{*}	0.0193^{***}	0.0195^{***}
	(-3.05)	(-2.37)	(-2.31)	(3.77)	(3.79)
Media Exposure (Sustainability Related)		0.00806^{**}	0.00919^{**}	0.00605^{*}	0.00678^{*}

		(2.67)	(2.77)	(2.00)	(2.04)
First-time Reporting		0.0237**	0.0283***	0.0252***	0.0289***
		(3.08)	(3.63)	(3.31)	(3.75)
Reporting Frequency		0.0237**	0.0278***	0.0254**	0.0291***
		(3.00)	(3.33)	(3.24)	(3.53)
IMR				0.114***	0.117***
				(4.47)	(4.57)
Constant	0.0243	0.0140	0.0137	-0.340***	-0.345***
	(0.80)	(0.43)	(0.41)	(-4.00)	(-4.03)
Industry Dummy	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes
N	1031	1031	1031	1031	1031
R^2	0.184	0.198	0.212	0.217	0.227
adj. R^2	0.106	0.118	0.134	0.138	0.150
F	2.352***	2.486***	2.714***	2.756***	2.932***

Note: *t* statistics in parentheses

2.4.3. Robustness Check and Endogenous Concern

We conducted additional analyses to check the robustness and address concerns about endogeneity. First, although the event studies were conducted with matched samples and eliminated unintended factors (Ketokivi & McIntosh, 2017), we examined whether the sample and control groups are well-matched by conducting a t-test of the data for the base year. The results show no difference between the sample and matched control firms for each dependent variable ($p > 0.1$). Second, we report on three types of tests to understand the median and mean changes for a robustness check, which reduces the concerns of data distribution and improves robustness.

Third, following prior studies, in addition to OLS based on a setting of industry and year fixed effects, we conducted regression analyses using Robust Regression (RLM), which enhances robustness by downgrading the influence of uncommon data (Longoni et al., 2019; McDermott et al., 2009; Pagell et al., 2015). Prior empirical research suggests robust regression as it assigns appropriate weights to ensure influential observations do not have undue effects on the results, which helps ensure the results are stable and unbiased (Ben-Jebara & Modi, 2021). The results are summarized in Tables 2.5 through 2.7. The RLM results show that the main effects of variables are consistent with the OLS results. All values of variance inflation factors (VIFs) for our independent variables are less than 6, well below the common threshold value of 10, indicating that multicollinearity is not a serious concern for this study (Belsley, 1980; Greene, 2003).

Fourth, given that the collected sample includes events from 19 years and firms in our sample have self-selected to release their sustainability reports, it was a concern that the occurrence of events may be non-random, leading to endogeneity issues (Arora et al., 2020). Sample selection bias might exist as we sample firms' GRI data that might have similar performance outcomes. Due to the non-randomness, the OLS estimation might be biased because independent variables can be correlated with the error term in the regression model (Antonakis et al., 2010). To deal with this endogeneity, we used the Heckman two-stage procedure to deal with potential sample-induced endogeneity (Arora et al., 2020; Heckman, 1979; Wiengarten et al., 2019). We collected the non-sample observations and performed a probit model that includes firm size, firm performance, and industry performance to predict the likelihood of firms conducting SR to estimate the inverse Mills ratio (IMR). The selection model is Pr (GRI_Reporting = 1) = Φ (*γ_0 + γ_1 Firm_Size + γ_2 Sample Perf + γ_3 Industry_Perf + ε).* The results of the regression models with IMR are shown in Tables 2.5 through 2.7. After correcting the endogeneity of self-selection (IMR variables show significance), the main explanatory variables remained unchanged. Finally, we controlled the time effects and industry effects by adding dummy variables (Lo et al., 2018). The results suggest that the possibility of endogeneity and endogenous selection bias is addressed.

2.5. DISCUSSION AND IMPLICATIONS

2.5.1. Discussion of Findings

The findings of this study are important in several ways. First, we show that GRI reporting not only sends signals to external stakeholders to improve market performance, it also somehow drives labor productivity. That means the *costly signaling effects from GRI reporting* apply to external and internal stakeholders and could reverse the signals created by their interactions that affect goals and efforts among operational employees. Second, despite its demand and additional risks and costs, we show it is of value for firms with underlying quality to adopt GRI reporting. The event studies show that GRI reporting firms in the US achieved better abnormal profitability (ROA), operational performance (*labor productivity* and *COGS*/*Sales*), and market responses (*Tobin's q* and *market value*) than non-reporting firms. Third, we show that the positive performance effects of GRI can last several years. The abnormal performance was achieved up to Year two from the year before GRI reporting was adopted. This reflects a long-term abnormal performance, which helps justify investment in a stringent and demanding SR standard like GRI. Fifth, while time-lag effects may apply to other signals, the Year 0 in our event study (first-time reporting) reflects a significant turning point when signal quality and strength started to work.

The event study also suggests that long-term profitability (ROA) caused by first-time GRI reporting in our data came from both labor productivity and market value, while

COGS/sales and *Tobin's q* play a marginal role or have a shorter term effect. This reassures us that GRI is not just a marketing communication tool: it is a tool for driving productivity. By integrating stakeholder theory, we argue it is the observability that informs external stakeholders and as a response external stakeholders can send "reverse" signaling to demand labor productivity as well as market performance. The market is not a pure signal receiver. It must have observed the first-time reporting and responded through market valuation with a "costly signal" demanding greater labor productivity. First-time GRI reporting is a declaration to external stakeholders of a firm's commitment to sustainability (external interaction), but it is also an invitation to scrutiny and a higher expectation (through the "reverse" signal effect), causing internal stakeholders like senior managers and operational employees to feel they are being scrutinized and they must demonstrate operational efficiency (internal interaction) as a signal of quality or strength.

Our explanation depends on the *observability* of GRI reporting. The regression results further verify that first-time GRI reporting is positively related to ROA. The results add nuances to the event study, that the effects of first-time reporting are effective for labor productivity but not *COGS/sales*, and effective for *Tobin's q* but not market value. The same nuanced differences also apply to reporting frequency. This could reflect demand from the external stakeholders or that prioritization created by internal interaction drove our sample firms to focus on labor productivity and *Tobin's q* to achieve ROA while improving sustainability performance in subsequent reporting. On the contrary, media exposure seems to drive ROA, but has no effect on any market response and operational efficiency measures, probably because it focuses on external interactions but does not drive internal interactions through "reverse" signaling effects.

2.5.2. Theoretical Implications

This study challenges the assumption that SR acts as signal quality and strength that affect only market valuation. This is a narrow assumption that restricts theoretical understanding. Signaling theory should be integrated with stakeholder theory to explain not only signals sent to external stakeholders that affect market performance, but also the effects of SR on interactions between external and internal stakeholders. We believe these interactions drive internal stakeholders to improve operational efficiency. That also means studies that explaining signaling effects must consider observability that allows costly signals sent to external stakeholders to come back to the reporting firms through the "reverse" signaling process. This leads to the need for an open system perspective that explains the interactions between internal and external stakeholders by integrating stakeholder theory. The implication is that studies that link SR to market performance should explain how the reporting firm interacts with different external stakeholders to define performance targets, such as operational efficiency. The integration of stakeholder theory and signaling theory following our integrated framework has the potential to expand the theoretical understanding of this phenomenon. By further explicating the process of "forward" and "reverse" signaling, we can better understand how internal and external stakeholders interact to drive sustainable operations.

The theoretical implication is not confined to sustainable operations literature. The results indicate that internal and external interactions might exist to facilitate the "forward" and "reverse" signaling processes through increasing observability or transparency. While we know transparency matters for accountability (Panwar &

Suddaby, 2021), the integrated framework opens a number of new research questions and an agenda to link sustainable operations to corporate and stakeholder governance. By explicating the internal and external interactions and demonstrating that they can drive bidirectional signals and sustainable operations, our integrated framework complements studies that explicate the process of stakeholder governance and accountability (Wong et al., 2021) and corporate governance (Bae et al., 2018; Ching & Gerab, 2017). The integrated framework can be extended such that sustainable operations literature can inform corporate and stakeholder governance literature.

5.3 Implications for Practice

Our results highlight that the benefits of GRI reporting are not limited to market performance alone, and that GRI reporting is not just a PR exercise. GRI reporting should be an integral part of sustainable operations because it drives a commitment to improve operational efficiency as a signal to suggest a firm's ability to absorb and gain efficiency from investing in a costly and demanding SR standard. A firm should view GRI reporting as an ongoing interaction with external and internal stakeholders. By recognizing pressures to improve sustainability performance (Luo & Bhattacharya, 2006) by listening to shareholders (Flammer, 2015) and shareholder activism (Flammer et al., 2019), internal stakeholders such as operational managers of the firms who are involved in SR reporting can use such insights and pressures to drive operational efficiency and profitability. The implication for practice is that a firm should involve operational managers and recruit important stakeholders such as suppliers as contributors in the preparation of GRI reports (rather than as a PR exercise) because they will learn to improve asset and labor utilization while meeting sustainability requirements.

We suggest that firms adopt stringent standards like the GRI guidelines because it is not only a powerful way to differentiate a firm's underlying quality from its competitors: *first-time GRI reporting* also acts as a burning platform, driving the "reverse" signal and motivational effects that increase efforts to increase transparency, accountability, and sustainable operations. This effect will drive *reporting frequency* and the need to produce consistent signals for increasing observability and improve performance as expected by the external stakeholders. Our results also suggest that top executives should not put all their attention into share market valuation and invest only in media. While there is no harm in cooperating with the media to enhance the observability of GRI reports, we do not find significant effects on either market response or operational efficiency. Although media and shareholders are likely to scrutinize practices based on the released sustainability information in the reports, *media exposure* appears to drive little of the "reverse" signaling effect on operational efficiency.

5.4 Limitations and Future Research

As with all studies, this study has its limitations. First, even though our additional analyses address the potential endogeneity caused by sample selection, our data cover only publicly traded manufacturing firms in the US with available GRI data. It remains to be established whether our findings can be generalized to small and medium enterprises (SMEs) that are not listed, capable of meeting GRI requirements, or operating in other contexts. To shed light on this question, future studies might consider combining different methods (i.e., surveys, interviews, case studies, simulation, etc.) to collect the operations data of SMEs that may not be available in the current data set. Second, this study is premised on signaling theory, which only considers positive signals to reduce information asymmetry, but we cannot account for mechanisms such as honesty and reliability perceptions (Connelly et al., 2011). As sustainability reports include rich unconstructed text, future research might consider exploring the changes in firm practices with the use of advanced techniques (e.g., natural language processing, data mining, etc.) to further determine the fulfillment of commitments in affecting firm performance. Third, this study focuses on the effects on performance of several attributes of voluntary SR. It does not include motives for conducting SR and the mechanisms in the purported "reverse" signaling effects. Future research may consider exploring motives for conducting sustainability reports, thereby generating insights into the drivers of GRI reporting. Last, future research might wish to examine how GRI reporting may drive the implementation of sustainability practices, especially how signal observability due to GRI reporting and other forms of sustainability reporting encourage employees of reporting firms to initiate sustainability practices in their operations. Considering the negative consequences of sustainability incidents, the combined roles of sustainability reporting and other environmental management standards and practices deserve future study.

3. CHAPTER 3: EVENTMINING: IDENTIFYING SUSTAINABILITY EVENT CASES USING NATURAL LANGUAGE PROCESSING

3.1. INTRODUCTION

Over the last decades, companies have been criticized for their adverse environmental and social impacts due to energy consumption, induced emissions and pollution generation. Firms are under increasing pressure to develop sustainability strategies and work proactively to be environmentally and socially responsible (Villena & Dhanorkar, 2020; Xu et al., 2021). Such strategies include the appointment of corporate sustainability executives as part of their top management teams to develop strategies and address sustainability issues (Arora et al., 2020). A key role of these executives is to understand and manage sustainability-related events that may influence firms by identifying and observing potential events. News is the key information source to identify the events, as it enables to managers observe the evolving events, public views, and relevant development related to the company. Event study is therefore considered an important tool and methodology for managers and researchers to gain insights about the events.

In order to conduct an event study, event identification is the first and most important step to identify timestamps and the companies involved (Ding et al., 2018). Currently, however, the event identification process heavily relies on how well managers can detect events that may influence firms. In the ever-changing market, systematic analysis of events cannot be effectively conducted without innovative approaches to reveal events that may have impacts on firms. Moreover, existing methods of event identification are often confined to single event recognition and fail to take account of a collection of events. Single event study makes managers difficult to gain insights holistically and overlook the other events that may also have impact on the company. Also, the discovery of important events may be delayed since the identification of events and data collection is conducted manually and retrospectively. The inefficient event discovery undermines managers' capacity for making foresight strategies, thus missing business opportunities or appropriate response to threats and opportunities.

To address these limitations in event identification, this study designed an *EventMining* approach based on state-of-the-art Natural Language Processing (NLP)[3], to help managers identify events that involve companies. By developing the *EventMining* approach, this study makes the following contributions. First, to meet the practical needs of managers and researchers, the proposed method can automatically identify clusters of events. Beyond the traditional retrospective single-event investigation approach, we offer a novel event identification solution in the form of clusters of events from news. Second, the proposed *EventMining* approach is efficient and adaptable, benefitting from the unsupervised machine learning setting[4]. It enables timely insights with less time lag for the event identification process. Lastly, the proposed approach allows multiple event identifications. It reduces bias of focusing on a single event.

The proposed *EventMining* approach includes four main modules, namely data monitoring (automated news scarping and store), preprocessing, clustering, and event

3 The relationship between NLP and machine learning: While NLP and machine learning can be considered two overlapping fields, in recent years, fields such as NLP and computer vision have become more independent, and machine learning is considered a classical concept or research of pure machine learning problems.

[4] Unsupervised machine learning and adaptation: we focus on unsupervised machine learning as its feature the training set with finetuned labels are not required. This provides additional adaptation in the ever-changing environment such as the market.

cases illustration. The proposed approach generates a series of potential events with significantly less human intervention. To the best of our knowledge, this is the first study that proposes an approach to advance the recognition approach for event studies with artificial intelligence features.

The remainder of this chapter is organized as follows. In Section 3.2 we review the literature using event study relating to firms' operations and their main features of event recognition. Section 3.3 presents the technical design of the *EventMining*, followed by the application of verification as Section 3.4. Lastly, in Section 3.5, we discuss the implications of the proposed approach for theory and practice.

3.2. LITERATURE REVIEW

Event identification is an important task for event studies. The event identification is a process of determining the time and companies involved relating to an event, that provide the essential information for event studies. Currently, the identifications of events are only the manual way which relies heavily on human judgment. To identify an event, researchers and managers need to manually search for announcements related to a specific event from the news (Ding et al., 2018). With the growing volume of online information, the existing event identification approaches are inefficient due to the limited human ability to process large and complex textual data. As a result, the exploration of events is limited and retrospective.

3.2.1. Event Study Methodology and Applications

Event study method is primarily used to determine the impact of an event, such as an announcement, activity, or incident. The event study method was first introduced in the 1960s (Fama et al., 1969) to use models to estimate the expected returns of participating firms at a specific point in time. Abnormal Returns (ARs) are calculated by examining the difference between expected and actual returns bring upon by the events. The typical procedure for an event study includes a) event definition, b) sample selection, c) data collection, and d) event analysis. Over the past seven decades, the evolution of event study methodology focuses on the development of alternative models for estimating returns. The alternative models for event study analysis include market model (Scholes & Williams, 1977), mean-adjusted model, market-adjusted model, Fama-French three-factor model (Fama & French, 1993), and Fama-French four-factor model (Carhart, 1997).

The event study research method has been a popular research method applied in various business disciplines such as operations and supply chain management, management information systems, marketing, etc. (Ding et al., 2018; Konchitchki & O'Leary, 2011; Wang & Ngai, 2020). However, the applications and insights of event studies are challenged by two limitations, namely the focus of single event and time lag of the findings. Referring to Table 1-1, the extant event studies focus on one specific event, and conclusions are drawn based on the event. However, in real-life cases, multiple events often take place and interact in affecting the company. Thus, investigation of a single event and its impact is inappropriate, neglecting other events that may affect the sample firms at the same time. This is not ideal as firms may overlook important events that may also influence their operations and performance.

Another limitation is that event studies often take a long time to reach findings of a new event, which is a time lag of insight. As shown in the Table 3.1, the existing event literature took an average of 12.33 years from the first occurrence of the event to reach results for a new event. Due to the nature of the ever-changing market, the lagged insights might not be used by managers to tackle timely issues in today's business environment. Since event identification relies on researchers undertaking manual work, the enormous time use can also lead to inefficiencies, especially when companies should respond in timely manner in an increasingly competitive and fast-changing business environment (Forbes, 2019).

Apart from the lack of efficiency and capability, manual event identification is vulnerable to human bias and errors due to subject evaluations, as it relies on researchers to read and collect a large number of news articles to manually establish a sample. Therefore, it is necessary to address the manual work of event identification and improve the efficiency of the study to gain timely insights.

Table 3.1 Events recognition in the event study literature

Author(s)	Field	Event	Data period	Sample size	Event identification approach	Time lag[a]
(Ba et al., 2013)	OSCM	Environment initiatives and innovation	1996-2009	261	Researchers manually recognized announcements of global green vehicle innovation were recognized by the researchers from company news (Factiva) to study its effects on the stock market reaction	17 years
(Brandon-Jones et al., 2017)	OSCM	Reshoring	2006-2015	37	Reshoring announcements were compiled by researchers through keywords search in Factiva.	11 years
(Dam & Petkova, 2014)	OSCM	Environmental supply chain sustainability	2005-2011	66	Environmental supply chain sustainability program announcements were recognized by researchers.	9 years
(Fan et al., 2020)	OSCM	Capacity-reduction initiatives	2011-2016	173	A sample of 173 capacity-reduction announcements from Chinese manufacturing firms is recognized by researchers for conducting event studies.	8 years
(Girotra et al., 2007)	OSCM	R&D projects	1994-2004	132	Researchers use the ADIS database and Factiva to identify the dates of drug failures.	13 years
(Hendricks et al., 1995)	OSCM	Capacity expansion	1979-1990	128	Announcements of decisions to increase capacity, collected by researchers from the Main source: Trade and Industry index, Dow Jones News Service, and PR news wire.	16 years
(Hendricks & Singhal, 1996).	OSCM	Quality award	1985-1991	91	Firms that have won the quality award, identified by researchers using a keyword search from the main source: Trade and Industry index, Dow Jones News Service	9 years
(Hendricks & Singhal, 1997)	OSCM	Product introduction delay	1984-1991	101	Researchers identified firms that have delayed their product introduction.	13 years
(Hendricks & Singhal, 2003)	OSCM	Supply chain glitches	1989-2000	519	Researchers searched announcements about production delays or shipping delays from the Main Source (Dow Jones News Service, Wall Street Journal).	14 years

(Hendricks et al., 2009)	OSCM	Supply chain disruptions	1989-1998	307	Researchers compiled a sample of supply chain disruptions from the announcements via the main source: Wall Street Journal, Dow Jones News Service.	20 years
(Jacobs et al., 2010)	OSCM	Environmental initiatives and awards	2004-2006	780	Two categories of announcements were identified by researchers from business news, including 417 announcements of corporate environmental initiatives and environmental awards and certifications.	6 years
(Jacobs, 2014)	OSCM	Voluntary emissions reduction	1990-2009	450	450 announcements of voluntary emission reduction from 1990 to 2009 were recognized and collected by researchers from the following main source: Business Wire, WSJ, PR news wires, Dow Jones News Service.	24 years
(Jacobs & Singhal, 2014).	OSCM	Product development restructuring	2002-2011	165	165 announcements of product development restructuring from 2002 to 2011 were recognized by researchers from the main source: Wall Street Journal, Dow Jones News Service.	12 years
(Jacobs & Singhal, 2017)	OSCM	Catastrophic disaster	2013	39	39 publicly traded global apparel retailers were identified by researchers in the event study.	4 years
(Xia, Singhal, & Peter Zhang, 2016)	OSCM	Product design awards	1998-2011	264	264 announcements of design awards given to commercialized products were recognized by researchers from Factiva and LexisNexis.	18 years
(Zhao et al., 2013)	OSCM	Product recalls	2002-2011	42	42 product recall announcements from 2002 to 2011 were recognized by researchers in the event study by researchers.	11 years
(Wiles & Danielova, 2009)	MKT	Product placements in films and television	2002	126	A number of 126 product placements in successful films during 2022 were recognized by the researchers.	7 years
(Homburg et al., 2014)	MKT	major channel expansions	NA	240	The researchers recognize 240 firms' announcements about major channel expansions from ad hoc disclosures, press releases, and articles across the Chinese, US, and Germany contexts.	NA
(Chen et al., 2009)	MKT	Product recalls	1996-2007	153	A number of 153 (passive and proactive) product recalls are identified by researchers.	13 years
(Elberse, 2007)	MKT	Casting announcements	2001 - 2005	1258	The researcher identified 1258 announcements of movie casting announcements from movie market reports.	6 years

(Leone et al., 2021)	AF	SEC enforcement	2003 - 2014	842	The researchers recognized 7649 accounting restatements from reports. After excluding the missing information (such as ticker symbols), a sample consists of 842 announcements are adopted.	18 years
(Yue et al., 2022)	AF	BC senators	1995-2017	43034	This researchers created a sample of 43034 senators on the Senate Banking Committee (BC senators) for evaluating its impact on bank opacity.	27 years
(Bartov et al., 2002)	AF	Meet or beat current analysts' earnings expectations (MBE)	1983-1997	64872	The researchers collected a sample consists of firm-quarter observations on the Thomas/First Call database of analysts' forecasts.	19 years
(Chatterjee et al., 2001)	MIS	Appointments of chief information officers (CIOs)	1997-1998	96	A number of 96 announcements of CIO appointments are recognized by the researchers.	3 years

Note: all of the above event studies rely on researchers to recognize samples of events; the time lag indicates the time difference between the first event and the time of insights got published; AF is accounting and finance; OSCM is operations and supply chain management; MKT is marketing; MIS is management information systems.
a. Time lag: The time gap between when the event first occurs and when the insight published.

3.2.2. Event identification in Artificial Intelligence

Recent developments in Artificial Intelligence (AI) technology transforms many tasks faced by human, such as auto-pilot, intelligent fake news detection. Regarding event identification, the common sources of event data for managers and researchers are news and announcements that are textual data. As such, the relevant AI field is Natural Language Processing (NLP), focusing on developing models of language and textual data. Based on textual data analytics and machine learning models, NLP can be used for data collection and dataset/database creation, and data preprocessing and analysis, therefore replacing parts of manual work for handling textual data previously performed by human researchers. Regarding event studies, NLP techniques such as web scraping, textual data preprocessing, and textual data analytics, can be useful for enhancing the efficiency and capacity of event identification.

Web scraping (also known as web crawler) is an innovative and emerging way for researchers to conduct data collection to create unique dataset. The approach uses algorithms to automatically access and collect data from a target site and store the data in a database. Unlike using data from established public databases, web scraping provides a way to create unique data set with high efficiency. Recent studies have used web scraping to create a dataset to create datasets. For example, in the field of healthcare operations management, recent research used web scraping to collect physician review and patients' opinions data from an online physician review website (Ko et al., 2019). Another recent study used web scraping to collect from online platforms and create a unique dataset of job posting, enabling examination of research questions related to work-from-home caused by Covid-19 and the impact on firms' operations (Ge et al., 2022). With the development of web scraping algorithms, researchers are able to access targeted online sources and collect the required data in a short period of time, which provides a capability that cannot be achieved by manual data collection. In event studies, scholars and managers need to access and collect event samples (e.g., news and announcements) that take a long time to create an event dataset. Based on the developed program, web scraping can request and parse the target text data from the HTML[5] information of the event website. Web scraping can replace manual work by automatically accessing data sources of the events. In this study, we propose a web scraping module that uses news data as a data source for event identification. Unlike the traditional event identification process, the proposed approach is able to collect and analyze news data in an efficient way to gain insights.

Regarding the news data analytics, the existing NLP and machine learning literature has been using news data as the data source for predicting the stock price movement (e.g., Ding et al., 2020; Ding et al., 2014; Duan et al., 2018; Schumaker & Chen, 2009) or forecasting the returns (e.g., Liang et al., 2013; Qin et al., 2017; Ruiz et al., 2012). The stock price movement literature usually considers the prediction as a classification problem that has three predictable binary labels (i.e., rise, drop, and bumpy), fitting three stock price movement strategies (i.e., sell, buy and hold); while the forecasting literature focus on the estimation of the stock price changes. Overall, these studies

[5] HTML: HTML is the abbreviation of HyperText Markup Language, which is a standard language for web pages.

focus on the task of increasing the accuracy of predictions and forecasting, rather than on event identification. Yet, for management scholars and practitioners, exploring the characteristics of the events is valuable since strategy developments need deep understanding of the events.

In this study, unlike previous studies that used classification or estimation algorithms to analyze the data of company news, we consider clustering algorithms that categorize the vectorized news data into event clusters. In contrast to classification models that aim to categorize data into a certain set of categories, the clustering algorithms categorize data into a flexible number of categories. Thus, new knowledge on events can be obtained based on the new clusters generated, satisfying our requirement to identify unknown events. In summary, this study aims to contribute to the three literature streams, including even study methodology, data-driven research, and management research. Table 3.2 summarizes the research gaps in the three existing literature streams, and how this study addresses the gaps to advance event identification approach. In addition, this study emphasizes the importance of understanding events rather than focusing only on predictions.

Table 3.2 Summary of research gaps

Streams of literature	Method	Gaps	This study
Event study Methodology	Manual event identification	Single event Lack of efficiency and capacity Lack of development of event identification methods	Consider the event identification as a clustering problem for additionally interesting management insights Provide a novel way to launch event studies by advancing the current manual event identification method
Data-driven research using company news	NLP and machine learning models for classification problems	Lack of understanding on the events contained in company news Lack of providing management insights	Beyond using company news data for forecasting or prediction, the focus of this study is to gain an understanding of the content of the extracted events. This study provides managerial insights for managers about the potential events in the market based on the explainable output of the model
Management research using textual analytics	Web scraping for data set development	Lack of applications of textual analytics on event study research	Provide an integrated framework of NLP-based event identification for supporting managers' decision-making. Enrich the development on management research and disruptive innovation, i.e., artificial intelligence.

3.3. METHODOLOGY

To address the limitations of existing event identification methods, we propose to develop *EventMining* that automates a series of tasks using an unsupervised machine learning setting. *EventMining* consists of four main modules. First, the news scarping module provides functions of collecting the online information. Second, the textual preprocessing module achieves the goals of textual data vectorization and corporate name recognition. Third, the event clusters are recognized based on a clustering module. Lastly, the results of event identification are demonstrated and visualized for managers for managerial insights. The procedure of *EventMining* reflect how machines can automatically identify events to replace the efforts of human researchers. Figure 3.1 depicts the main procedure of *EventMining*.

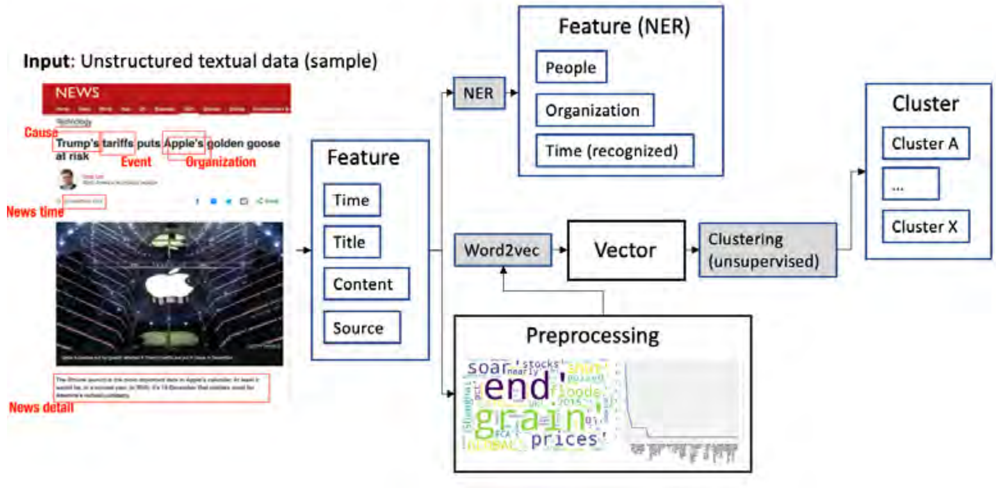


Figure 3.1 The main procedure of the EventMining event identification

3.3.1. News Scraping

To access, collect and store the news data from online sources (e.g., Reuters company news) automatically, we develop the news scraping module based on web scraping techniques. News scraping enables researchers and managers to collect large amounts of updated data from online data sources with less manual work. In this study, we apply that web scraping for news data collection to identify relevant events of firms.

The news scraping program includes three parts, namely requesting, parsing and storing. First, for each target information source (e.g., company news), the target

URLs[6] were generated and input into a queue[7]. By doing so, the requesting program accesses the news pages iteratively and requests the data. An error diagnosis mechanism[8] was designed and incorporated in the program to avoid disruptions when the websites cannot be accessed (e.g., timeout, missing data, etc.). Second, after accessing the website, the web scraper scans the HTML[9] document, which is the source code that includes all information displayed on the web page, and stores the document as a temporary file[10]. Third, a parser program was developed to retrieve target information from the stored temporary HTML files using Regular Expression. The parsed information about the news (i.e., headline, content, timestamp, etc.) was stored as a data set for the data processing modules. However, the procedure of collecting data sources may have errors due to multiple reasons such as unstable Internet and server access. Similar to the requesting program, an error diagnosis mechanism is incorporated to ensure the program can be executed continuously. The mechanism verifies whether the collected data is correct and complete before inputting them into the database. The news scraping program is developed using Python (version 3.8) in this study. Figure 3.2 depicts the workflow of the news scraping program.

---

[6] URL: Uniform Resource Location, the link for accessing a website page.
[7] URL Queue: a queue (list) generates needed URL using a specific rule.
[8] Error diagnoses mechanism: In some cases, the news scraper may not able to access the information in the website due to multiple reasons, such as time-out, frequent access, etc. Diagnose mechanisms and strategies are used. The main idea of the diagnose strategies is to check the collected information and raise exceptions to avoid uncompleted data. In later rounds, the news with uncompleted data will be recollected automatically. These designs consider the real situations that the Internet information might not complete all the time and increase the robustness.
[9] HTML: Hypertext Markup Language, the format of a website page.
[10] Temporary file is a file created for storing the intermediate results for data parsing.

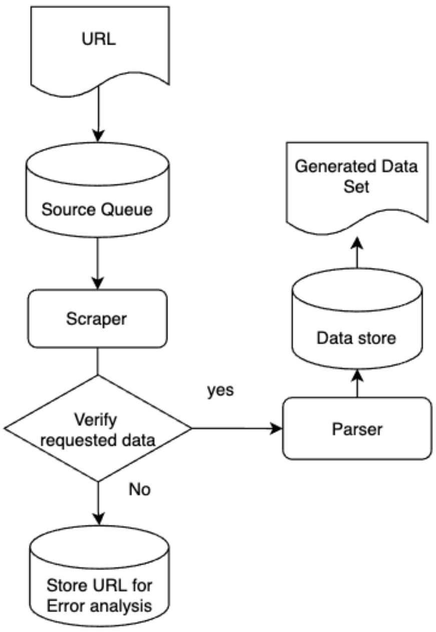


Figure 3.2 News scraping workflow

(a) sample web page

```
<meta name="title" content="McDonald&#39;s creates new team with hire of chief global impact officer" />
<meta name="medium" content="news" />
<meta name="date" content="2020-10-01" />


<meta name="twitter:card" content="summary_large_image">
<meta name="twitter:domain" content="Restaurant Dive">

    <meta name="twitter:site" content="@restaurantdive">


<meta property="og:title" name="og:title" content="McDonald&#39;s creates new team with hire of chief global impact officer" />
<meta property="og:site_name" name="og:site_name" content="Restaurant Dive" />
<meta property="og:type" name="og:type" content="article" />
<meta name="article_date_original" content="Thursday, October 01, 2020, 09:55 AM" />
<meta property="og:url" name="og:url" content="https://www.restaurantdive.com/news/mcdonalds-creates-new-team-with-hire-of-chie
```

(b) HTML info of the web page

Figure 3.3 Example of web information access

Referring Figure 3.3, we illustrate how the news scrapping program retrieves data from an online news article. In general, news consists of three key sections that attracts readers' attention and therefore trigger market's reactions, i.e., News Headline (including the summary of the fact), News Time (the timestamp of the news published), News Content (the main content of the news including the details for reading). As shown in Figure 3.3, we retrieve three pieces of important data from the web page as the target information, i.e., *News Headline* (i.e., "McDonald's creates a new team with hire of chief global impact officer"), *News Time* (i.e., Oct 1, 2020), and *News Content* (i.e., McDonald's has created a …"). The HMTL data (see Figure 3.3) was accessed by the requesting program. Then, the target data is retrieved by the parsing program as data for data analyses and event identification.

3.3.2. Data Preprocessing

After collecting and storing news data using the news scraping module, the preprocessing module process and clean the data for preparation of analyses. The module has three functions, including tokenization, named entity recognition (NER), and data cleaning. Preprocessing of news data is crucial for NLP applications, as the data is unstructured text. Comparing to common data in a numerical format, the textual data is difficult to be interpreted by machine learning models, because lots of semantic information and complicated relations among different parties are included. Therefore, preprocessing is an important procedure for an NLP task.

Text Preprocessing. News articles includes rich textual data, which is a combination of words in a designed order. Since textual data includes flexible and complicated semantic information, the machine learning models cannot process and interpret the input news data directly, leading to difficulty for analytics. To address this, we adopted four main preprocessing techniques. First, sentence splitting, which is a process of dividing the texts into sentences, is straightforward task to process news data that includes more than one sentence. However, in news data, the symbols such as "." may not be placed consistently, leading to problems to break the sentences incorrectly. To address this issue, this NLP function uses a syntax tree to detect the completeness of a sentence and avoid missing semantic information. The sentence splitting function is useful for addressing the news data which generally includes multiple sentences. Second, tokenization is the process of turning the input text into individual objects (i.e., tokens). The tokens can be characters, strings, sub-words, words, etc. They are the unit of text for vectorization. The understanding of tokenization can be straight forward. It is an essential work for NLP models as it determines the granularity of NLP models, reflecting how the semantic and edge information can be retained, and ensures the complexity of computing is reasonable. Using the pre-trained annotated model, the tokenizer can break up the news into word-level tokens.

Third, part-of-speech (POS) tagging is a function designed to assign POS labels to tokens, to determine the attributes of each token. The POS tags are given based on Penn Treebank, which is a useful and widely accepted POS tagging rule for NLP research (Marcus et al., 1993; Taylor et al., 2003). Appendix 1 shows the full description of the POS tagging rule defined by Penn Treebank. Lastly, lemmatization (lemma) is to map a word to its lemma in order to reduce the redundancy of tokens that cause large but useless vector dimensions. The large size of vector dimensions will cause curse of dimensionality, which is phenomenon in which the computing complexity increases exponentially as the number of dimensions increases. For instance, the word “creates” was mapped to its lemma “create”. Overall, these preprocessing functions are useful in processing the news data and ensure the data is clean and explainable.

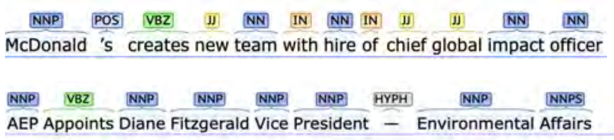
Company ticker symbol identification. An event consists of two key information, time and company involved. To recognize an event, identifying the company names and their ticker symbols is an important step. Regarding financial news, though some of them indicate the company names directly, it is common that companies’ name will be included in the content of news article in different forms. When collecting news data from web pages, the ticker symbols of the companies (as unique identification) involved in the news data are however often not available. Before linking the events and companies, it is necessary to recognize the company names involved in each news. To enable this, a function was developed to recognize company names from the texts, based on named entity recognition (NER) [11] . Specifically, we adapted the StandfordNLP model, which is a state-of-the-art NER model based on statistical learning developed by the Stanford NLP group (Manning et al., 2014). The annotator categorized the tokens into 12 different entities, including named entities (PERSON, LOCATION, ORGANIZATION, MISC), numerical entities (MONEY, NUMBER, ORDINAL, PERCENT), and temporal entities (DATE, TIME, DURATION, SET). As shown in Figure 3.4, the organization names can be recognized correctly from the input texts. Furthermore, the company names are matched with their ticker symbols, which are unique symbols to identify companies in the market. As such, the event companies involved in each news are recognized.

Stop-word List. Machine learning methods train models and parameters by learning features of the input data. In the *EventMining* approach, we aim to train the models based on an unsupervised setting. Compared to supervised learning methods, due to the lack of ground truth labels[12], unsupervised learning models are more sensitive to the input data. In other words, unsupervised learning models are more dependent on

---

[11] Named entity recognition (NER): As mentioned in the previous sections, named entity recognition is one of the important tasks of the natural language processing. The main of objective is to recognize the attributes of each entity for the input textual data.
[12] Ground truth labels: Ground truth labels are correct labels checked by human one by one for a dataset. It is used for training supervised models as the learning objectives.

high-quality input data because they receive less information during the training process. Therefore, it is essential to ensure the data is clean and reduce the disturbance. For the task of processing textual data, as its high unstructured feature, some words may occur with a high frequency, e.g., “says”, “is”, “be”. However, these words are likely to have a low contribution to the correct interpretation of the news (Hardeniya, 2015; Hardeniya et al., 2016). To address this, the stop-word list, a dictionary that can be used to recognize redundant words during the preprocessing procedure, is implemented



(a) tagging

(b) NER

Figure 3.4 Visualized example of POS and NER result

3.3.3. Text Clustering and Topic Demonstration

Text Vectorization. As news is unstructured data that cannot be used as the input for the typical machine learning models, it is necessary to convert the input textual data as vectors, which are numerical representations of the semantic information. term frequency/inverse document frequency (TF-IDF) model is used to represent the input sentences in a vector space. TF-IDF is to calculate the term frequency (TF) and inverse Document Frequency (IDF) (Jones, 1972; Salton & Buckley, 1988). Specifically, TF aims to calculate the word frequency, where IDF is a weight of how the words are unique in a document. In general, TF-IDF converts the input texts into vector representations using the most representative words in the documents. The formulas are listed as follows:

$$TFIDF = TF \times IDF \tag{3.1}$$

$$TF(t, d) = \frac{count\ of\ t\ in\ d}{number\ of\ words\ in\ d} \tag{3.2}$$

$$IDF(t) = \log\left(\frac{N}{df(t)}\right) + 1 \tag{3.3}$$

where TF is term frequency; IDF is Inverse Document Frequency; t is term; d is document; N is the number of documents in the corpus; $df(t)$ is the number of documents in the corpus contain the term.

Event clustering. Clustering is one of the typical machine learning problems, which aims to divide data into a number of meaningful groups. Clustering categorizes data into the same groups when they have similar patterns[13] (similarity) and separate data that are dissimilar into different groups (dissimilarity), based on the distance of the vectors. In this study, K-means is used as a model for vector clustering because it is straightforward and efficient. K-means plays the role of a baseline model in the many variants of the clustering models, so it is a good candidate for initializing the system design. Given an input sample as *x(1), ..., x(m), x(i)* $\in$ *Rn*, a number of k cluster

[13] Pattern is a common description in the computer science (machine learning) work. It refers a regularity in the world or in an abstract concept. In our setting, it refers the data with some underlying relationships and links.

centroids as $\mu 1, \mu 2, ..., \mu k \in Rn$ will be selected randomly. Then, the datapoints will be assigned to the closest cluster center according to the distance. After that, for each cluster j, the cluster centroids will be reset as new datapoints involved, and the datapoints will be assigned to the new cluster center iteratively. When the centroids become stable and unchanged, the results of assigned labels to each datapoint will be finalized. In the event clustering, we adopt the clustering approach to assign a cluster label to each news. The formulas are shown as follows:

$$c^{(i)} := \arg\min_{i} \left\| x^{(i)} - \mu_j \right\|^2 \tag{3.4}$$

$$\mu_j := \frac{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\} x^{(i)}}{\sum_{i=1}^{m} 1\left\{c^{(i)} = j\right\}} \tag{3.5}$$

where x is input sample as x(1), ..., x(m), x(i) ∈ Rn; μ1,μ2,...,μk represents centroids, refers to the index of each cluster.

3.4. APPLICATION, EVALUATION AND RESULTS

To apply the proposed *EventMining* approach, we employed news data retrieved from Thomson Reuters, consistent with the setting of the existing NLP literature (Ding et al., 2014, 2015). Over the period of 2011 to 2017, there are 210 thousand news related to various companies. Using sustainability-related events as a sample, we purify the news data set using a keyword list[14] to focus on sustainability news domain and

14 Consistent with Xu et al. (2022) we use a list to help focus on sustainability-related news for the analysis of media exposure, which consists of important keywords of sustainability. The keyword list we used is as follows: ['environmental', 'environment', 'environmental disclosure', 'social responsibility', 'global reporting institute', 'GRI', 'corporate social responsibility', 'CSR reporting', 'sustainability', 'sustainable', 'sustainability performance', 'environmental reporting'].

minimize the interference of data noises, consistent with prior research (Xu et al., 2022). Table 3.3. shows a sample of the input data.

Table 3.3 Data sample

ID	Timestamp (year/month/day) (numerical)	News Headline (textual)	News article (textual)
1	20140502	Airlines exempt from Sept. 11 environmental claim -US court	NEW YORK May 2 American Airlines United Airlines and the World Trade Center leaseholder do not have to pay a property developer environmental cleanup costs from the Sept. 11 2001 hijacked plane attacks a US appeals court ruled on Friday.
2	20110907	Glencore's 1st sustainability report shows 18 deaths	LONDON Commodities group Glencore released its first sustainability report on Wednesday showing it paid $780 000 in major environmental fines last year and had 18 fatalities.
3	20111229	Libya Eni review regards two social programmes-Eni spox	MILAN Dec 29 A spokeswoman for Italian oil and gas group Eni said on Thursday a contract review announced earlier by Libya regarded two social sustainability programme agreements and not oil contracts.
4	20160627	BRIEF-Goldcorp releases 2015 sustainability report	Goldcorp releases 2015 sustainability report Source text for Eikon: Further company coverage:
…	…	…	…

To make the unstructured textual data prepared for analyses, the *Text Preprocessing* module processed the data set with Sentence Splitting, Tokenization, POS Tagging and Lemmatization. The Stop-word list was applied to exclude the redundant words that may disturb the results. We adapted the NLTK stop-word list, which is a list including the most common words that widely accepted for many NLP tasks. Adding to this setting, we also use descriptive analyses of work frequency and distribution. Using a ranking based on the frequency of words, we adjusted the NLTK stop-word list and further help the model to remove redundant words. Figure 3.5 shows the general information and the word distribution of the dataset. Table 3.4 shows the count results based on the word frequency of the dataset, used to adjust the Stop-word List.

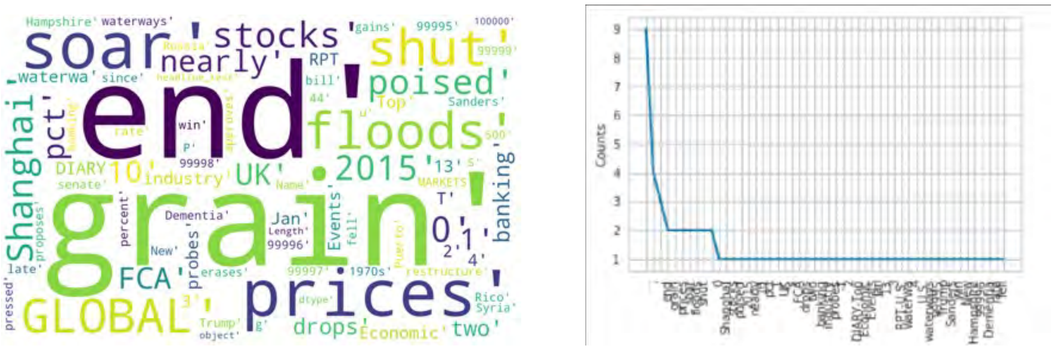


Figure 3.5 Word cloud and distribution

Table 3.4 Word frequency labeling for stop-word list development

Word	Frequency	Stop-word label	Word	Frequency	Stop-word label
[('said'	590)	1	('co'	217)	0
('corp'	554)	0	('thursday'	213)	1
('us'	508)	0	('york'	212)	0
('environmental'	500)	0	('emissions'	211)	0
('new'	437)	0	('state'	185)	0
('environment'	364)	0	('tuesday'	183)	1
('inc'	329)	0	('refinery'	183)	0
('oil'	320)	0	('billion'	255)	0
('pollution'	313)	0	('green'	251)	0
('company'	294)	0	…	…	…

After cleaning the input data, the *Text Preprocessing* Module vectorized the unstructured news data into vectors with a dimension of 50.

Figure 3.6 illustrates the processed datapoints in the space. Event data point refers to a news that include the information of time and involved companies. Notably, the vectors have a dimension of 50, representing the rich semantic information expressed by the news. In the next step, the *Text Clustering* module will categorize the vectorized data into k clusters to discover event cases.

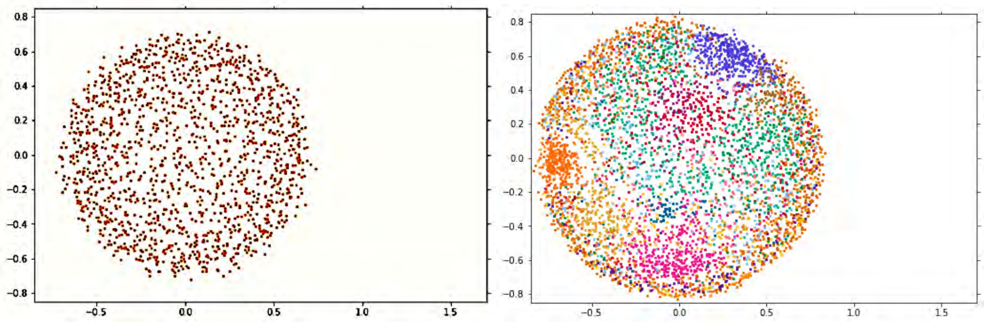


Figure 3.6 Visualization of vectorized data

The *Text Clustering* module categorize the news data into a number of k clusters. Consistent with the existing literature (Yang, et al., 2022), we employ silhouette score (Rousseeuw, 1987) as the metric for evaluating the reliability of clustering results. The silhouette score (s_i) is calculated using the mean intra-cluster distance (a_i) and the mean nearest-cluster distance (b_i). For each sample, s_i will be calculated as the $s_i = \frac{b_i - a_i}{\max(a_i, b_i)}$, ranging from -1 to 1. The higher the silhouette score, the more certain that we can believe the estimated cluster labels are corrected, whereas negative scores indicate a sample assigned to the wrong cluster (Rousseeuw, 1987). As shown in Figure 3.7, the silhouette score increases and converges while the cluster number k increases. When k equals to 120, the silhouette score s_i reached the highest value (s_i = 0.074) and converged (the change of s_i is not significant when k continues to increase). Therefore, we chose to categorize the data into 120 clusters.

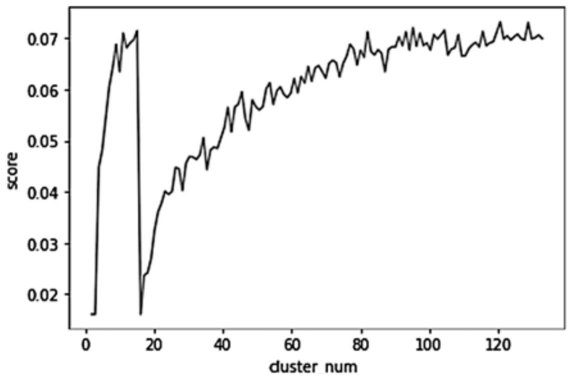


Figure 3.7 Evaluation of cluster results

Figure 3.6 also visualizes the clustered data points. It is worth noting that the data points are mapped from higher dimensions to two dimensions for visualization. The data points are able to be distinguished by the clustering model in higher dimensional based on distance. A set of 120 event clusters were generated based on the *Text Clustering* Module. So far, *EventMining* has identified the event clusters with the content, time and company information, representing *what, when and who* which are three key information for an event. We then consider the identified event clusters as event cases and conducted qualitative interpretation for managerial insights. To check the robustness of the interpretable results, the following design was used:

Table 3.6 presents a sample of interpretation result (event cases No. from 1 to 6). Event case 1 is an event related to environmental debates about oil transportation that involves two pubic-trading companies BP (BP plc) and TC (TransCanada Corporation) from 2011 to 2014. Two companies were identified as having six timestamps for their information. This event case reveals that the environmental debate on oil pipeline has been long existing. In 2011, TC was involved in an emotionally environmental debate because of a proposal to build cross-country oil pipeline. In 2016, the project Keystone XL was involved in a similar type of event as the proposal of developing an oil sands pipeline from Canada to US. Details can be found in Table 3.6, row 3. Event case 2 (Table 3.6, row 2) is related to environmental lawsuit. Two companies, CVX (Chevron Corporation) and TM (Toyota Motor Corp Ltd), were involved in this type of event case over the period from 2011 to 2016. The output of Event case 2 captures a series of environmental lawsuits involving Chevron, even if they occurred in different years. The event case indicates, back to 2011, Chevron had been involved in a lawsuit about pollution in the Amazonian rain forest. An update released in 2013 about the judge decision on the related lawsuit case. In 2016, Toyota Motor Corp was affected by a lawsuit case in India about older diesel vehicles off New Delhi's roads.

Event case 3 (Table 3.6, row 3) represents a case about environmental incident, pollution, and maintenance. Five companies that include BP, COP, CVX, VLO, XOM and fourteen timestamps were identified. Specifically, this event case reveals that, starting from 2011, these companies reported the flaring warning, which are pollution activities affecting nearby areas. In addition, some flaring was expected and are environmental incidents. Event case 4 (Table 3.6, row 4) reveals a series of activities related to pharmacy retailing activities. Most of the data into this case relates to the Walgreens Boots Alliance Inc and Target Corporation. Event case 5 (Table 3.6, row 5) relates to market estimation announcements. Six public-trading firms and eleven timestamp were identified. Event case 6 (Table 3.6, row 6) represents environmental investment, such as Investment Cessation, investors' concerns, green bond issuance. Sixteen public trading firms and sixteen timestamps were identified. Similarly, the remaining event cases represent different types of events that matter firms' operations. The interpretation of the full list of event cases are shown in Appendix IV. Thus, the effective identifications on the three key elements of event case demonstrate that the approach is valid for event identification.

Robustness check. We aim to verify that whether the machine-generated event cases indeed help identify event cases. Additional analyses and evaluations were implemented to ensure the validity and robustness of the results, including evaluations on the clustering performance and human check for the machine-generated results. The evaluations and checks for machine learning models can be categorized into external validation and internal validation. "External clustering validation and internal clustering validation are the two main categories of clustering validation. The main difference is whether or not external information is used for clustering validation (Liu et al., 2010, p. 911)." Specifically, the internal validations are assessed based on metrics built on the relationships among the datapoints (e.g., Silhouette Coefficient), where external validation is assessed using metrics based on the objectively correct answer defined by external information (e.g., accuracy), known as the ground truth labels that has been widely used in the literature (Bauman & Tuzhilin, 2022; Wei et al., 2019). However, external information (e.g., ground truth labels[15]) is often not

[15] Ground truth label: the true and correct answer about which datapoint belongs to which cluster (Liu et al., 2010).

available in many application scenarios of unsupervised clustering analyses (Liu et al., 2013). In the context of this study, the input data is online company news without any class label. Also, for the scenario of a large number of clustering, human inspectors are not capable to provide ground truth labels to all news correctly (Liu et al., 2010; Liu et al., 2013). As such, internal validation is the first option considered for evaluating the proposed approach. In our study, the internal validation of clustering performance was evaluated using the Silhouette Coefficient s_i, which measures of how similar an object is to its own cluster compared to other clusters (Rousseeuw, 1987). Higher values of the score indicate a good fit of the generated clustering results (Rousseeuw, 1987; Yang et al., 2022). Ranging from -1 to 1, negative values generally indicate that a sample is assigned to the wrong cluster (Rousseeuw, 1987). A value near 0 indicates an overlapping cluster. The empirical results find the optimal Silhouette Coefficient (s_i) is 0.74 while the number of clusters is 120, indicating the clustering results has good internal validation that is consistent with the recent literature (Yang et al., 2022)[16].

Although internal validation was first considered to evaluate the generated event cases, while ground truth labels were not available in the context, we designed and implemented a procedure of external validation based on manual checks, to do so, we conduct manual check based on a human inspector who have management knowledge. The following steps were implemented to achieve the validation goal. Step 1: Content

[16] Optimal: Optimal indicates the highest value of the score in the context of the metric silhouette coefficient.

of sample clusters[17] generated for human interpretation. Step 2: Making human judgements based on identifications of the content of each event cluster. The content of the news articles will be presented to the human inspector for interpretation. An event cluster is defined as a group from which contains content related to a similar event topic. We present the content of each cluster one-by-one and ask the human inspector to give binary answers. After reading the news articles presented, the human inspector needs to give answer to the following question: "Based on the articles shown, how many events can you identify?" a) There is *one event* based on the articles shown; b) There are *two events* based on the articles shown; c) There are *three or more events* based on the articles shown. d) There is *no event* based on the articles shown. Step 3: Evaluating the validation results. As shown in Table 3.5, the results indicate that 90 clusters (75.0%) were identified as a single event, indicating that most event clusters generated have correct representations of an event. Furthermore, 12 clusters (10.0%) and 5 clusters (4.2%) were identified as two events and three or more events, respectively. This result indicates that machine put more than one events into one cluster set and consider they are relevant. In addition, 13 clusters (10.8%) do not show a clear logic as to why this data should be considered as a cluster of events. Through this design, we are able to evaluate whether the machine-based identification is robust. As such, we use manual check on the event clusters to externally validate the results generated. Based on the above checks, we verified the results of generated event cases through both internal and external validation.

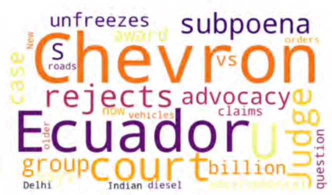
[17] Sample of Content: In practice, if the amount of input data (text data) is deemed too large for manual checks, a validation set can be generated based on a sampling of the content of the input data.

Table 3.5 Statistics of clustering evaluation

Number of clusters	Accuracy (%)	Description
One event	90 (75.0%)	There is one event can be identified based on the content of news in a given cluster.
Two events	12 (10.0%)	There are two events can be identified based on the content of news in a given cluster.
Three or more events	5 (4.2%)	There are three or more events can be identified based on the content of news in a given cluster.
No events	13 (10.8%)	There is no event can be identified based on the content of news.
Total	120 (100%)	-

Note: The number of events is the clusters can be identified by human inspector from each event cluster generated.

Table 3.6 Event cases found from the clusters

Cluster	Word Cloud Visualization “Keywords for reference”	Event time (Year-level) “When”	Event time (Date-level) “When”	Involved Companies “Who”	Event cases found “What”
1		2011, 2014	20140327 20111031 20111101 20111102 20111111	BP, TRP	*Case 1: This event case is related to environmental debates about oil transportation.* Keystone XL is an oil sands pipeline from Canada to the central US that proposed by BP in 2014, which trigger the concerns of environmentalists. Similarly, TRP involves in an emotional environmental debate because the proposal of cross-country oil pipeline in 2011.
2		2011, 2013, 2016	20130403 20130403 20110919 20110920 20130412 20160718	CVX, TM	*Case 2: The event case is related to environmental lawsuit.* First, in 2011, US appeals court reversed an order freezing enforcement outside of Ecuador of an $18 billion damages award against Chevron Corp over pollution in the Amazonian rain forest. In 2013, Judge rejects Chevron subpoena of advocacy group in Ecuador case. However, Chevron says Ecuador environmental claims now in question. On the other hand, in 2016, another firm TM is involved into an environmental lawsuit. Indian court orders older diesel vehicles off New Delhi's roads, which affected the company Toyota Motor Corp.

3		2011, 2012	20111111 20120318 20120325 20120704 20110828 20111009 20110828 20120221 20120205 20120212 20120415 20111016 20120610 20120708	BP, COP, CVX, VLO, XOM	*Case 3: Environmental incident/pollution/maintenance* This event case is related to environmental pollution - Flaring. From 2011 to 2012, BP plc, ConocoPhillips, Chevron Corporation, Valero Energy Corporation, Exxon Mobil Corporation reported several times warns of pollution – flaring.
4		2015, 2016, 2017	20160706 20151117 20151117 20151117 20150212 20150212 20150212 20150921 20150921 20151215 20160211 20160211 20160405 20160517 20160609 20160609 20160706 20160706 20160829 20160829 20160829 20170105	CVS, KSS, TGT, WBA	*Case 4: Pharmacy retailing activities* This event case includes a series of activities related to pharmacy retailing. Most of the activities related to the leading pharmacy company Walgreens Boots Alliance Inc and Target Corporation.

5		2011, 2012, 2013, 2014, 2015	20110920 20150623 20150623 20141008 20110816 20120827 20121019 20150120 20150120 20120724 20120717	ACN, BAC, BRRY, BCS, ERIC, GEB, MS, SAP, STT	*Case 5: Announcements of Market Estimations.* This event case relates to market estimations and outlooks. Market estimations related to the six companies were released in years from 2011 to 2015, respectively,
6		2011, 2013, 2014, 2015, 2016, 2017	20111011 20160217 20160511 20161101 20111129 20151007 20160608 20160907 20160802 20170111 20160727 20150729 20160509 20140528 20130425 20110819	AA, AAPL, AMZN, BA, BCS, BLK, BP, DUK, EMR, HSBC, KO, MS, STO, TSLA, UN, WMT	*Case 6: Investment* This event case includes a series of investment events. For example, Norway's fund barred from investing in U.S. firm Duke Energy. Statoil to get rare respite from green criticisms at AGM.

Note: The full table of 120 clusters are included in Appendix IV.

3.5. DISCUSSION

3.5.1. Methodology Implications

This study has several important contributions to methodology of event study research. First, to our knowledge, this study is the first research to address the manual work of event recognition. The proposed *EventMining* approach changes the traditional way of event identification to a large extent. Based on the state-of-the-art NLP techniques, we advance the event identification, that is an essential task for every event study (Ding et al., 2018). Several most advanced technologies have been used for event identification. By integrating web scarping technology, the method automatically collects company news data from online information sources and identifies key information about events. Company names and stock symbols can be automatically identified. Based on text clustering, potential events clusters can be identified in an unsupervised manner. Through evaluating the parameter of the cluster number, our application on real-life data set show that the *EventMining* approach is effective in discovering multiple event cases. The interpretation of event cases shows that these findings are highly comprehensible for management insights. Therefore, by mining events in textual information, researchers can be relieved from laborious and inefficient manual work for event studies.

Second, the proposed approach provides managers with an innovative way to explore multiple events in the marketplace, rather than a single event. The proposed *EventMining* discover multiple event cases involving different companies over a time period. Although management scholars have long used event research methods to understand events, the lack of development of identification methods has limited their capacity to focus on events from an integrated perspective. The proposed method fills this gap by allowing retrieval of multiple events from input news data. As a result, researchers and managers can use the proposed model to gain in-depth insights.

Third, *EventMining* approach provides automated event identification with less researchers' intervention, which is helpful in addressing the post hoc focus of existing event studies. Prior literature provides a range of findings based on identified events, yet all studies take several years to generate management insights on a specific event (Ding et al., 2018). The lack of solutions on how to address the lead time between events and insights has resulted in barriers to knowledge transfer from theory to practice. By addressing the ability of event identification, this *EventMining* can address the lead time for event research. Thus, the proposed approach accelerates event research by speeding up event identification, resulting in rapid insights.

In addition, this study sheds light on the machine learning literature by emphasizing the significance of discovering the event cases from the unistructural textual data. In the past, machine learning scholars have focused on using company news to improve the predictive performance of stock prices. Most of the models developed aim to learn the labels of the data and improve the predication result. These "black box" models have gained limited management insight because the events contained in the news events are ignored. This study provides a new pathway for machine learning scholars from a management perspective that it is important to discover explainable patterns of events and possible causal relationships before considering only prediction problems.

Thus, machine learning researchers can combine event research models to provide models that can provide management insights for practice.

3.5.2. Managerial Implications

Our research has also had a significant impact on managers. Our research has driven the application of event research, making it accessible to managers at different levels. Event research was previously a research method rather than a practical tool because event identification was highly dependent on the interest and recognition of the researcher. With the proposed NLP approach to event identification, the identification task is no longer the exclusive work of researchers, but more pragmatically can be handled by managers at different levels. Training managers to do research is difficult, but implementing programs is more practical. Thus, this study makes event research a more practical tool that can help managers to take advantage of it.

At the same time, the proposed methodology provides a solution for managers to create their "event portfolio". Previously, a key reason why event research had fewer application scenarios for managers was that it focused on a single event, which did not fit the needs of managers focused on the industry or market. Events tend to appear concurrently rather than coming individually. Unlike traditional event identification, our approach allows managers to focus on multiple events occurring in different industries. With a broader view of events, managers are able to gain a comprehensive understanding.

3.5.3. Limitations and Future Directions

Bridging NLP and event studies is a new and exploratory task, which is an iterative process. This demand works to provide innovative changes and updates. This study has several limitations that should be acknowledged for future research. First, although we implement the state-of-the-art NLP techniques in the proposed approach, the model can still identify the event based on the word level (i.e., bag of words), leading to missing full semantic information. Future research may extend the framework of this study by developing or applying advanced NLP models to address the features at a semantic level, which is also an important task in the AI field.

Second, *EventMining* methods generate potential event clusters from the collected news. Although the proposed approach overcomes many limitations of traditional event identification methods (e.g., multiple events, more efficient discovery, low human bias), high-quality labels and metrics are not available due to the unsupervised setting. Future research can extend the proposed framework by focusing on the use of supervised and semi-supervised machine learning models (with real labels and domain knowledge for that task).

Third, although event clusters are identified through the use of *EventMining*, it is also valuable to assess the impact of the identified events. Therefore, the impact and importance of the identified events can be emphasized, which can provide implications for researchers and managers for strategic development. Therefore, future research could consider extending the proposed methodology and linking it to event analysis.

By automating the entire process of event research, data-driven event research can provide more desirable research results that can be used directly by researchers and managers.

Finally, we use visualization features to help users understand the meaning of the identified clusters. However, automatic functions for event summarization are not available in the current framework. The abstraction model can further reduce the time to interpret the event content, thus speeding up the event identification process and reducing the lead time for event research. Further research could consider techniques for implementing document summarization, which is an important subfield of NLP and AI. By achieving this goal, the developed models can help researchers interpret events, further improving effectiveness and efficiency.

4. CHAPTER 4: MANAGING THE UNEXPECTED: A LARGE-SCALE DATA-DRIVEN EVENT ANALYSIS ON EMERGING SUSTAINABILITY EVENTS

4.1. INTRODUCTION

"*We started questioning and challenging everything. The traditional ways of planning are outdated. We sense every hour, every day, every week, and react to it*." said Fernando Gonzalez, CEO of CEMEX, a global leader in the building materials industry, in response to the recent violate business environment (IBM, 2021).

Developing sustainability strategies has been one of the most important planning needs for companies in recent years (Arora et al., 2020). Sensing and understanding sustainability events in the investors and stakeholders' concern are the pathways to achieving this goal. However, the development of sustainability strategies faces challenges in a volatile, uncertain, complex, and ambiguous (VUCA) market (Forbes, 2019), where events continuous to evolve and affect firms and/or their supply chain partners. This change of the market requires firms to focus on the Emerging Sustainability Events (ESEs) to formulate strategies, which we define it is the sustainability events in the formation process. According to this definition, ESEs are expected to have three main characteristics: they occur in the early stages of the effect; they may have small sample sizes; and they are visible to investors and may lead to market reactions. Unlike the sustainability events that attract a high volume of attention from researchers and managers, the ESEs are, indeed, a series of events that may easily be overlooked due to their emergent nature. Yet, the ESEs may have significant impact on the firms, industries and market. In order to cope with the potential impacts of ESEs, learning about *what* and *when* the events trigger the market are crucial to firms.

Event study has been using by researchers and managers to gain insights into sustainability events and their impacts (Ding et al., 2018). Prior literature investigated environmental management awards/crises (Klassen & McLaughlin, 1996), environmental program initialization (Dam & Petkova, 2014), voluntary emissions reduction (Jacobs, 2014), environmental-related certification (Treacy et al., 2019), environmental incidents (Lo et al., 2018), and sustainability reporting (Xu et al., 2022), etc. While the existing literature has explored the effects of various sustainability events, the investigation of ESEs that beyond the known sustainability events, remains a research gap.

Compared to gaining understanding on sustainability events explored in the literature, the ESEs may play more important roles as the insights in a good timing, before the storms formed, are crucial for firms' operations to reduce risks and catch opportunities. The important ESEs may continuously signal the concerned investors and stakeholders and eventually trigger significant reactions in the market and society. The ESEs may involve various supply chain participants in the market that include the peers, upstream buyers, and downstream suppliers of the firms. For example, a firm's upstream suppliers can be involved in sustainability incidents or lawsuits reported by local media. From 2011 to 2012, four major energy companies in the US, BP Inc., ConocoPhillips Inc., Chevron Corp., and Exxon Mobil, had 15 incident and maintenance reports. Most of them relates to flaring, which is a planned or unexpected pollution affects the neighborhood air quality. The events like this may have an influence on the neighborhood environment and market reaction. However, these ESEs may not be able to be noticed by downstream firms.

Gaining insights on ESEs is not an easy task. Unlike the sustainability events largely explored in the literature, ESEs are easily to be overlook by researchers and managers because there so many events are forming and occurring. Multiple ESEs may appear or cease in the market, making the manual identification and estimation on the ESEs not practical. However, managers, not only who work in the affected firms, need to understand *what* the market concerns (i.e., ESEs) and *when* it happens in order to better position their companies and to develop rapid and proactive strategies. Innovative solutions are called for to the challenge of gaining insight into ESE.

To address the ESEs, we aim to provide answers to the questions of *what* and *when* regarding the effects caused by ESEs. We study the impact of ESEs using the firms' stock market price, which is a widely accepted market performance indicator used to statistically determine the significance of an event (Ding et al., 2018).The following two Research Questions (RQs) were examined:

> **RQ1:** *What are the Emerging Sustainability Events (ESEs) that significantly affect the stock market?*

RQ2: *When do the Emerging Sustainability Events (ESEs) trigger the stock market reactions?*

The nature of ESEs calls for innovative solutions. The main source of ESEs is company news, which contains rich unstructured text data. To discover the patterns of these data, we employ Event-Mining, a NLP-based event identification approach, for conducting multiple event identifications based on company news (Xu & Wong, 2022). To achieve the empirical goal of examining multiple ESEs, we design a Data-driven Event Analysis (DDEA) system for automated event study analysis. Based on the results of 120 event cases found, the large-scale event study reveals that (1) ESEs with continuous effects[18] and (2) timeline of ESEs' impacts[19]. Regarding the events with continuous effects, we find that the market was sensitive to and reacted to 12 types of ESEs based on the input sustainability news data, which relate to Brazilian mining, sustainability in Australia, Chevron litigation, medical, experimental and environmental activities, environmental funding activities, environmental regulation, environmental regulation and policy in New Jersey, approvals and support, refinery breakdowns and maintenance, environmental project start-ups and challenges, and plant-related activities. Regarding the timeline of ESEs' impact, the results show that, on the event day, the market reacts most significantly to ESEs related to refinery failures and maintenance immediately, followed by ESEs of sustainability financing issues, environmental regulation, sustainability events in Australia, Brazilian mining,

[18] ESEs with continuous effects: ESE that has a significant impact on the company's market performance during the event window.

[19] timeline of ESEs' impacts: Highlighting the most significant ESEs on a specific day in the event window. The DDEA system ranks the importance based on the abnormal return (AR).

Keystone related events, etc. On the day after the event day (day 1), the results show that ESEs with a lagged effect are sustainability financing events, Brazilian mining, and refinery failures and maintenance, etc. In addition, we explore the changes in market reactions to several ESEs, such as Monsanto's activities, sustainability trading and asset activities, environmental fines, and settlements, over a one-day window (Day 0 to Day 1). Over a window of five days (Day 0 to Day 5), the impact of ESEs such as emissions allegations, capital and market activity were changed significantly.

This research contributes to both the theory and practice of sustainability management in several aspects. To the best of our knowledge, this study is among the first to address multiple ESEs and quantitively compare their effects on the market reaction. We find that, although the observable samples are small, a series of ESEs have triggered significant market reactions. We provide answers about *what* and *when* about the important ESEs that trigger market reactions. These findings enhance the understanding of sustainability events by revealing the ESEs that have been overlooked by researchers and managers in the past. More importantly, managers are able to create their "proactively strategic portfolios" for sustainability planning and arrangements, as they are able to notice various ESEs in advance. Also, we find that sustainability events with similar types may trigger different market reactions. This is because although some ESEs appear the same to researchers when building theories, in practice, the market reactions can vary greatly when similar ESEs affect different companies in different contexts. Therefore, our findings suggest that managers should consider the effects of ESEs more precisely because the impact should be fine-grained[20]. In addition, this research provides researchers and managers insights on sustainability events that focus on multiple ESEs and their impacts rather than a single event, which is consistent with the situations of managers about decision-making in the real-world. This study also provides theoretical and managerial insights for conducting data-driven event research that address multiple sustainability events affecting their companies and supply chain partners.

The remainder of this study is organized as follows. Section 4.2 reviews the existing literature on sustainability events and the related work on methodology development of event study analyses. In Section 4.3, we present the methodology of event study analysis and dataset employed, followed by analysis results in Section 4.4. Lastly, we discuss the implications for both theory and practice in Section 4.5.

4.2. LITERATURE REVIEW

To frame our work, we consider the literature from the following streams: (1) event studies on sustainability (2) data driven research.

4.2.1. Event Studies on Sustainability

With the increasing awareness about the impacts of firms' production and operations on the natural environment, research on sustainability events has been one of the key

[20] Fine-grained event effects: A fine-grained understanding of the impact of events means that managers should consider events more precisely rather than having a general understanding of them. In NLP, granularity is a popular concept that refers the concept of "breaking down an event into smaller parts or granules such that each individual granule plays a part in the higher-level event" (Mulkar-Mehta et al., 2011, p. 360). In this study, we consider the fine-grained event is understanding the events more precisely rather than having a general understanding.

problems in the event study literature. To fulfill the expectations of stakeholders, firms have been undertaking different ways to address their negative impact on natural environmental and sustainability (Xu et al., 2021). A stream of studies has been focusing on the important factors that support managers' decision-making. By estimating the Abnormal Returns (ARs) of stock price, statistical results are employed to provide empirical evidence whether a sustainable event has an impact on companies' market performance. Most of sustainable event studies in the extant literature have focused on new and mature events to build theories. As shown in Table 4.1, prior research has examined the impact of initialization of sustainable programs on market response. Based on evidence from green vehicle innovations (Ba et al., 2013) and voluntary emission reductions (Jacobs, 2014), the market was found to have a positive response to environmental initiatives and innovations. In contrast, a negative impact on market value was found in environmental supply chain sustainability programs (Dam & Petkova, 2014). The above studies present different arguments for the market's response to the firms' environmental and sustainable initialization.

Awards and incidents are considered as explicit outcomes of firms' environmental practices. Environmental awards were found as an environmental outcome that positively affects firms' market value (Klassen & McLaughlin, 1996). Conversely, the negative effects on firms' financial performance were shown to come from incidents, including Environmental incidents (Lo et al., 2018) and crises (Klassen & McLaughlin, 1996). These studies conclude that investors are sensitive to the environmental performance and results of companies.

Companies has also been actively or passively conforming to different sustainability standards in the pursuit of its sustainability goals. Mandatory nonfinancial disclosure was found to have negative effects on the market value (Grewal et al., 2019), whereas voluntary reporting shows a positive impact on firms' profitability (Yang et al., 2021) and operational efficiency (Xu et al., 2022). Previous studies indicated that SA 8000 certification has a positive influence on firms' labor productivity (Orzes et al., 2017); ISO 14001 certification leads to better performance on cost efficiency, labor productivity and profitability (Treacy et al., 2019); and adopting the United Nations Global Compact has a sportive effect on firms' sales growth and profitability (Orzes et al., 2020). These findings suggest that firms can gain a competitive advantage by proactively fulfilling strict standards, although some mandatory requirements have shown a negative impact on firms' market performance.

Apart from analyzing the effects of sustainability events, research has also found these effects were influenced by specific moderators. Arora et al. (2020) found that appointments corporate sustainability executives do not lead to market reactions directly. However, when firms are facing prior adverse sustainability incidents, the stock market reacts more positively to the appointments. The context factors may also make a difference in the outcomes of sustainability events. Chinese investors consider corporate environmental initiatives negatively, which is different from the empirical evidence found in the Western context (Lam et al., 2016). Companies may also implement distinct strategies when they face a sustainability event. Hardcopf et al. (2021) reveal that firms will increase environmental management practices regardless the spill or pollution accidents. However, sustainability leaders do not alter their practices when they face these accidences, whereas non-sustainability leaders escalate their practices when they face a similar situation. Thus, although theories based on the results of event studies can guide managers in considering the impact of events in a general way, it is possible that the conclusions are not sufficiently granular.

Although previous studies have examined the impact of different sustainability events on corporate market performance, they have largely ignored ESEs. Indeed, to the best of our knowledge, no event study provides a comprehensive understanding of ESEs. However, in a violate environment that requires firms to strategize quickly, important ESEs identified at an early stage are important for managers to develop rapid competitive strategies to gain advantage and avoid risk. Therefore, our study aims to explore a series of ESEs and add the findings to the literature on sustainability event study research.

Table 4.1 The literature on sustainability events

Author(s)	Sustainability event	Effects (DV)	Key insights	ESE focused?
(Arora et al., 2020)	Corporate sustainability executives (CSE)' appointments	Shareholder value	Stock market reaction is more positive to the appointments of sustainability executives when firms are facing prior adverse sustainability incidents.	-
(Lo et al., 2018)	Environmental incidents	Market value (negative)	The announcements of environmental incidents lead to a significantly negative stock market reaction based on empirical evidence from Chinese market.	-
(Dam & Petkova, 2014)	Environmental supply chain sustainability programs (ESCSPs)	Market reaction (negative)	This paper revealed that there is a negative and significant stock price reaction to announcements of participating ESCSPs.	-
(Klassen & McLaughlin, 1996)	Environmental management awards / crises	Market valuation (positive to awards and negative to crises)	Management crises led to significant and negative market valuations, where the environmental management awards trigger positive market valuations.	-
(Lam et al., 2016)	Corporate environ mental initiatives announcements (CEI)	Stock market price (negative)	Chinese investors react negatively to CEI announcements, which is different from the previous findings in the Western context.	-
(Jacobs, 2014)	Voluntary emissions reduction (VER)	Stock market price (negative)	VER is positively associated with firms' stock market price.	-
(Jacobs et al., 2010)	Corporate Environmental Initiatives (CEI) and Environmental awards and certifications (EACs)	Market value (positive to awards and ISO 14001 certification and negative to voluntary emission reduction)	Market reacts significantly positive to environmental awards and ISO14001 but reacts significantly negative to voluntary emission announcements.	-
(Ba et al., 2013)	Environment initiatives and innovation (Green Vehicle Innovation)	Market value	Stock market generally reacts positively to automakers' announcements of environmental innovations.	-

(Jacobs & Singhal, 2020)	Volkswagen Emissions Scandal	Stock market price	The Volkswagen (VM) diesel emissions scandal leads to significant and negative market reactions to VM and their suppliers and non-VM partners experienced a positive effect.	-
(Hardcopf et al., 2021)	Spill or Pollution Accident	Adoption of environmental management practices (EMPs)	Spill or Pollution accidents do not alter firms' practice of EMPs.	-
(Grewal et al., 2019)	Mandatory Nonfinancial Disclosure	Stock price	A generally negative market reactions due to the increasing mandatory nonfinancial disclosure implemented by European Union (EU).	-
(Orzes et al., 2017)	SA8000 certification	Operations performance	This study found that SA 8000 certification has a positive influence on firms' labor productivity and sales performance but no effect on profitability.	-
(Orzes et al., 2020)	United Nations global compact (UNGC) adoption	Sales growth and profitability	This paper found that the UNGC adoption has significant and positive effects on firms' sales growth and profitability.	-
(Yang et al., 2021)	GRI reporting	Profitability	Based on 122 Chinese listed firms, this paper found that GRI reporting significantly increase firms' profitability.	-
(Feng et al., 2020)	Sustainability certification announcements	Market value	This study focuses on the question that whether Chinese enterprises can benefit from sustainability certification announcement as a legitimacy action.	-
(Treacy et al., 2019)	ISO14001 certification	Operations performance	The results show that ISO 14001 certification has a positive and prolonged effect on certified firms in terms of cost efficiency, employee productivity and return on assets.	-

4.2.2. Data-driven Research and Emerging Event Analysis

Looking at the broader literature, studies from different disciplines have proposed the use of data-driven approaches to solve problems. As we know, company news is the one of the primary data sources that often used by event study scholars to identify events. In recent studies, a stream of data-driven research has used company news as an important source of information to predict the market performance of companies. Since company news is textual data, currently, these studies are usually published in the field of Natural Language Processing (NLP) as part of the practice of how Artificial Intelligence (AI) can be applied to real-world cases (Bustos & Pomares-Quimbaya, 2020). The literature in this area can be divided into two types, namely stock price movement forecasting and earnings forecasting. The stock price movement forecasting problem is considered as a categorical problem that usually has three predictable binary labels (i.e., rise, drop, and bump) that fit three movement strategies (i.e., sell, buy, and hold) (e.g., Ding et al., 2014, 2015; Du & Tanaka-Ishii, 2020). On the other hand, the return forecasting problem focuses on the estimation of returns as a regression problem (e.g., Duan et al., 2018; Qin et al., 2017; Schumaker & Chen, 2009). These studies focus on the question of how company news can be used to improve the probability of predicting companies' stock price, rather than on empirical findings indicating possible causal relationships.

On the other hand, research is also examining questions about the prediction of public emergencies. Dorr et al. (2014) proposed a model to estimate the probability of events that occur in human conversations. Based on their results, the study showed qualitative evidence that some successful cases that emerging events could be retrieved from conversations, such as an emerging flood. In addition, Feng and Shah (2022) propose to predict public emerging events from multiple publicly available data, including census, twitter, and google trends. Based on the proposed framework, this study estimated Covid-19 cases and deaths in California. These studies explore how to retrieve possible public emergencies from user data. However, ESEs have not been examined.

Overall, AI research has been developing NLP models to use textual data as a source of information for prediction. This suggests that NLP analyzing company news data could be an innovative solution to replace human efforts to recognize events, which is in line with the setting of analyzing ESEs at a large scale. While previous research has explored data-driven analysis and public emergencies, the literature has not explored ESEs or revealed their effects on the market reaction. However, understanding these relationships is important for managers to develop better strategies. With the motivations, this study aims to explore ESEs based on company news and data-driven analytics.

4.3. METHODOLOGY

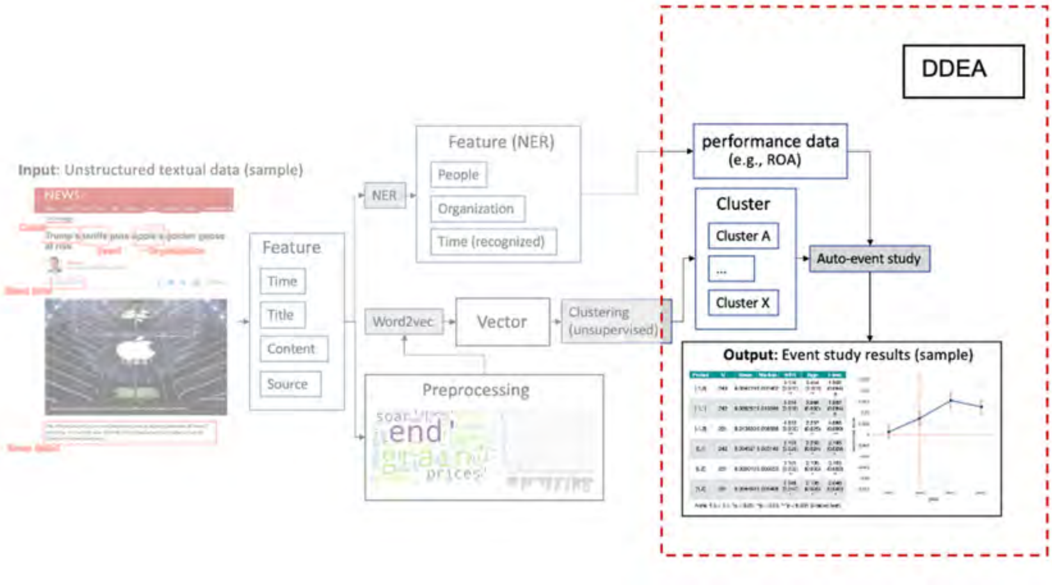


Figure 4.1 The integrated framework of EventMining and DDEA system

4.3.1. Retrieving Events from Company News

To understand ESEs and their impacts, first, we need to retrieve events from company news, which is the main source of ESEs. The design of traditional event identification driven by researchers can only focus on one specific event, which does not meet the requirements of emerging event analysis that should include multiple events. Therefore, we used EventMining, which an NLP-based event recognition method, to search a set of candidate ESEs (Xu & Wong, 2022). We used a Thomson Reuters Corporate News dataset, which includes 210,000 company news items over the period from 2011 to 2017. As shown in the conceptual framework in Figure 4.1, the news data was processed and the useful information were recognized using the named entity recognition (NER) module, such as organization and timestamp information. The contents of news were preprocessed and then converted to vectors. The clustering module groups news vectors with similar information into clusters. As a result, a set of 120 events are identified and prepared for the analyses in the DDEA system.

4.3.2. Event Study Methodology and DDEA System

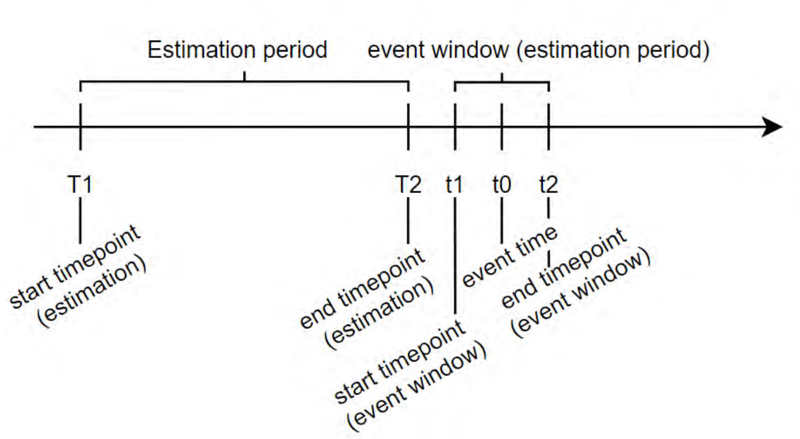
Not all recognized events are important ESEs. While ESEs are recognized using NLP-based event recognition methods, there is a need to determine whether the event triggers a market reaction significantly. Therefore, we extend the event identification framework by designing a DDEA system. Linking to the previous step of retrieving events from company news, our DDEA system automatically queries market data from Center for Research in Security Prices (CRSP) database to collect market data for companies. The organization and timestamp information were interpreted by the DDEA system to match needed stock market price data from the database. Also, the DDEA system collected the daily Standard and Poor's 500 (S&P 500) stock market data as one of the inputs for the event study models to calculate the reference performance. Based on this, a large-scale event study was conducted to analyze the impact of all recognized events. Also, the most important events are highlighted based on the statistical significance. Unlike traditional event studies, this study estimates a series of events by using algorithms to achieve results beyond the capabilities of a single researcher. The DDEA system automates event studies.

DDEA system estimates Abnormal Return (AR) based on the event study methodology. In the following subsections, we describe the procedure of event study methodology and describe how we automated each procedure as modules, including calculations of critical dates, Expected Return (ER) estimation, AR estimation and statistical significance (see Figure 4.2).

We developed the DDEA system using Python. The automated event study in DDEA can be summarized as several main tasks, including (1) critical data calculation, (2) Expected Return (ER) estimation, (3) Abnormal Return (AR) estimation, and (4) statistical analyses.

Critical Date Calculation

To determine the expected returns and abnormal returns for each event, five critical dates should be calculated and imported for analyses, i.e., t_0, t_1, t_2, T_1 and T_2 (see Figure 4.2). Specifically, t_0 is the event date. T_1 (e.g., day -60) is the start time of estimation period where T_2 (e.g., day -5) is the end time. The parameters of t_1 (e.g., day -2) is the start of observation period, which is two days before the event day. Accordingly, t_2 is the end of the observation period. As such, the event window is [t_1, t_2].



Timepoint	Description
t_0	the day of the event
t_1	the start day of the observation period
t_2	the end day after the observation period
T_1	the start day of the estimation period
T_2	the end day of the estimation period

Figure 4.2 Event study timeline

Unlike the traditional event study analysis, *DDEA* is able to query necessary data automatically. As such, when the recognized event dates are input, the module will calculate these critical dates for each sample. For the dates which are holidays and weekends, the module will use the following working days instead to avoid missing market data.

Expected Return (ER) estimation

The calculations of abnormal returns (ARs) are based on the expected returns (ERs), which is an adjusted performance according to firm's pervious performance and other factors such as market factors. We use the statistical market model to estimate the ERs. The formula can be found as follows:

$$E(R_{it}) = \alpha_i + \beta_i \cdot E(R_{Mt}) + \epsilon_{it} \quad (4.1)$$

where i is the index of stock; t is time.

The market model is the most widely adopted model to estimate ER, though there are various models to achieve this goal, such as market model (Ding et al., 2018). We select market model as the baseline model for AR estimations. First, the expected return. R_{it} needs according to the information during the estimation window. Second, $AR_{i,t}$ can be calculated based on the expected return R_{it} and information during the event window. Then, the statistical results can indicate whether there is a significant difference caused by the event by comparing the before and after AR_{it}. The main parameters are described in Table 4.2.

Table 4.2 Variable and parameter for short-term event study

Item	Description
R_{it}	Variable. The return of the observation i on the day t
ε_{it}	Variable. The return of the reference market on day t.
$AR_{i,t}$	Variable. The abnormal return of the observation i on the day t.
i	Parameter. Index of observation.
t	Parameter. Index of Day.
$\hat{\alpha}_i$	Parameter. The estimated expected return of observation i.
$\hat{\beta}_i$	Parameter. Estimated market return of observation i.

The market model (Scholes & Williams, 1977) predicts firms' normal returns based on an assumption of linear relationship between sample firms' return and the market portfolio. The calculation can be summarized as follows:

$$R_{it} = \hat{\alpha}_i + \hat{\beta}_i \cdot R_{mt} + \varepsilon_{it} \quad (4.2)$$

where $E(\varepsilon_{it}) = 0$, $var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$; R_{it} is the return of the observation i on the day t; R_{mt} is the return of the of the reference market on day t; ε_{it} is the error term (a random variable) with expectation zero and finite variance.

Abnormal Return (AR) estimation

The abnormal return AR_{it} is calculated based on the difference between the actual return R_{it} and expected return R_{mt} estimated based on the market model.

$$AR_{it} = R_{it} - \left(\widehat{\alpha_i} + \widehat{\beta_i} \cdot R_{mt}\right) \tag{4.3}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the OLS estimates of α_i and β_i for firm i estimated over the pre-event estimation period.

The $\overline{CAR_i}$ represents the average cumulative return of a firm over the event window.

$$\overline{AR_i} = \sum_{i=1}^{N} \frac{AR_{it}}{N} \tag{4.4}$$

where i is the index of sample firm; N is the number of sample firms on day t.

The $\overline{CAR}_{(t1,t2)}$ represents the average cumulative abnormal return of over the event window t1 and t2. $\overline{\overline{AR}}_{(T1,T2)}$ can be calculated as follows:

$$C\overline{\overline{AR}}_{i,(t1,t2)} = \frac{\sum_{t=t2}^{t=t1} \overline{AR}_{it}}{|t2 - t1|} \tag{4.5}$$

where t_1 is the start timepoint for estimation period; t_2 is the end timepoint of estimation period.

Statistical tests

Statistical models are used to examine whether the AR is significant. Depends on the property of the test, these tests can be categorized into two types, i.e., parametric test and non-parametric test. The t-test is a parametric test has been used in many of event studies (Ding et al., 2018). Relies on assumptions of independence and homoscedasticity, this approach examines the mean value among two groups. The formulas of t-test are shown as follows.

$$t_{AR_{i,t}} = \frac{AR_{i,t}}{S_{AR_i}} \tag{4.6}$$

where S_{AR_i} is an estimate of stand deviation of the average abnormal return.

$$S^2_{AR_i} = \frac{1}{M_i - 2}\sum_{t=T_0}^{T_1}(AR_{i,t})^2. \tag{4.7}$$

$$t_{CAR} = \frac{CAR_i}{S_{CAR}} \tag{4.8}$$

The Wilcoxon Signed Rank (WSR) test is a nonparametric test widely used in the event research literature. Unlike the t-test based on the mean, the WSR test measures significance of AR based on the median. To implement the data-driven features, statistical models are integrated into the event study module. The formula for the WSR test is shown below.

$$W_t = \sum_{i=1}^{N} rank(A_{i,t})^+ \tag{4.9}$$

$$z_{wilcoxon,t} = \frac{W - N(N-1)/4}{\sqrt{(N(N+1)(2N+1)/12)}} \tag{4.10}$$

Consistent with existing literature (Ding et al., 2018), we set up several event windows for examining the short-term effects of the events, i.e., day 0, 1, 2, 3, 4 5, period [0, 1], period [0, 5], and period [0, 10], period [0, 10]. Grounded in the estimation of market model (Scholes & Williams, 1977), the AR on day 0 represents the immediate effect caused by the event. The AR on day 1 to 5 reflects on the lagged event effects that may various because the nature of the event. Several periods, which measures the difference in AR between two event days, present three trends in events, short term (change within one day), medium term (change within 5 days) and long term (change within 10 days). By doing so, it provides a more detailed measure of the short-term impact caused by the event for managerial implications.

4.4. RESULTS AND ANALYSES

4.4.1. Event Study Results

We focus on five critical days and periods to measure the impacts of events, namely day 0 (event day), day 1, period [0, 1] (day 0 to day 1), period [0, 5] (day 0 to day 5), and period [0, 10] (day to day 10). Focusing on day 0, the results show that 15 ESEs had a significant effect on the market performance of the companies involved. The events with the most significant AR are sustainability glitches, finance, regulation, funding, program initialization, judgment and lawsuits activities. Ranking from 1 to 5, the event with index 52 (i.e., Refinery glitches and maintenance) has a positive and significant effects on firms' market performance (AR Mean = 0.021; $p < 0.01$; AR Median = 0.026; p_WSR < 0.01). The financial activities related to sustainability (index= 47) has a positive and significant effects on involved firms' market performance (AR Mean = 0.03; $p < 0.05$; AR Median = 0.025; p_WSR < 0.01).

Environmental regulation events (index= 38) have a positive and significant effects on market valuation of involved firms (AR Mean = 0.015, $p < 0.05$; AR Median = 0.010; p_WSR < 0.05). Sustainability events in Australia (index= 18) has a negative and significant effects on the involved firms' performance (AR Mean = -0.065; $p < 0.05$; AR Median = -0.047; p_WSR < 0.1). The events involving Brazil mining (index= 16) companies resulted to a negative and significant market reaction (AR Mean = -0.019; $p < 0.05$; AR Median = 0.019; p_WSR < 0.05).

Regarding the events with ranking 6 to 10, the sustainability events related to Keystone lead to a negative impact on the involved companies' market performance (AR Mean = -0.015; p< 0.05; AR Median = -0.016, p_WSR < 0.05). The sustainability fundings activities expose by media (index= 31) show a positive impact on involved firms' performance (AR Mean = 0.048; $p < 0.05$; AR Median = 0.046, p_WSR < 0.05). The media exposure related to environmental projects initialization (index= 62) has a positive effect on firms' market reaction (AR Mean = 0.009; $p < 0.05$; AR Median = 0.005; p_WSR < 0.05). The judgements on oil companies show a positive impact on involved firms' market reaction (AR Mean = 0.104; $p = 0.117$; AR Median = 0.042; p_WSR < 0.05); The lawsuit cases of Chevron (index= 13) have a negative influence on involved firms' market performance (AR Mean = -0.033, $p < 0.05$, AR Median = -0.036; p_WSR < 0.05).

The remaining events which have significant effects on firms' market reaction is related to environmental trading (index= 92; AR Mean = - 0.061; $p = 0.143$; AR

Median = -0.027; p_WSR < 0.1), Media exposure on medicine experiments and environment (index= 48; AR Mean = 0.034; p < 0.05; AR Median = 0.030; p_WSR < 0.1), and updates on environmental scandals of VM (index= 48; AR Mean = 0.034; p < 0.05; AR Median = 0.032; p_WSR < 0.1); In addition, the content of two events (index= 105 and 114) with significant impacts could not be explained easily, suggesting that attention should be paid to these ESEs as more evidence becomes available.

Table 4.3 Important events on day 0 (the event day)

Event Day(s)	Index	Event[21]	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	52	Refinery glitches and maintenance	19	0.021	0.026	0.024	0.002*	0.001**
0	47	Financing / Debt, sales, interests	18	0.031	0.024	0.046	0.007**	0.011*
0	38	Environmental regulation	10	0.015	0.010	0.017	0.014*	0.019*
0	18	Sustainability events in Australia	12	-0.065	-0.047	0.089	0.016*	0.028*
0	16	Brazil Mining	20	-0.019	-0.019	0.034	0.017*	0.024*
0	109	Events related to Keystone	9	-0.015	-0.016	0.016	0.020*	0.024*
0	31	Environmental funding activities	9	0.048	0.046	0.047	0.020*	0.016*
0	62	Environmental projects initialization and challenges	12	0.009	0.005	0.014	0.021*	0.044*
0	89	Sustainability judgment and oil company	9	0.104	0.042	0.177	0.027*	0.117
0	24	The lawsuit case of Chevron	13	-0.033	-0.036	0.049	0.033*	0.032*
0	92	Environmental trading	9	-0.061	-0.027	0.112	0.055†	0.143
0	26	Medicine experiment and environment	5	0.026	0.018	0.024	0.063†	0.072†
0	48	Environmental scandal and updates / VW case	6	0.034	0.030	0.032	0.063†	0.049*
0	105	NA	5	0.070	0.045	0.064	0.063†	0.070†
0	114	NA	9	-0.030	-0.021	0.044	0.074†	0.078†

Note: ***p < 0.001, **p < 0.01, *p < 0.05, † < 0.1 (two-tailed). NA means that the generated event cannot be easily interpreted by researchers. N is the number of observations.

On the day after the event day (i.e., day 1), 17 events were found significant effects on the involved firms' market performance. Among the clusters interpretable, the financial activities related to sustainability show a positive and the most significant

[21] The event column is based on interpretation of the recognized event clusters.

effects on the related firms' market performance (AR Mean = 0.035; $p < 0.05$; AR Median = 0.052; p_WSR < 0.05). Activities related to Brazil Mining industry show a negative impact on market performance (AR Mean = - 0.021; $p < 0.05$; AR Median = - 0.018; p_WSR < 0.01). The updates on Refinery glitches and maintenance show a positive effect on involved firms' market performance (AR Mean = 0.019; $p < 0.01$; AR Median = 0.027; p_WSR < 0.01). The sustainability events in Australia show a negative effect on the involved firms' market performance (AR Mean = -0.065; $p < 0.05$; AR Median = -0.039; p_WSR < 0.05). The environmental project initialization has a positive influence on the market performance of involved firms (AR Mean = 0.009; $p < 0.029$; AR Median = 0.005; p_WSR < 0.05). The remaining events (rank from 6 to 11) are related to events related to Keystone, environmental regulation, environmental funding activities, sustainability judgments, lawsuit cases of Chevron, environmental trading, environmental regulation and policy, environmental scandal and updates related to the VM case.

Table 4.4 Important events on day 1

Event Day(s)	Index	Event interpretation	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
1	59	NA	14	0.021	0.016	0.019	0.001	0.001**
1	47	Financing / Debt, sales, interests	18	0.035	0.021	0.052	0.002**	0.011*
1	16	Brazil Mining	20	-0.021	-0.018	0.038	0.007**	0.020*
1	52	Refinery glitches and maintenance	19	0.019	0.028	0.027	0.008**	0.007**
1	18	Sustainability events in Australia	12	-0.065	-0.039	0.088	0.012*	0.027*
1	62	Environmental projects initialization and challenges	12	0.009	0.005	0.012	0.016*	0.029*
1	109	Events related to Keystone	9	-0.015	-0.017	0.016	0.020*	0.029*
1	38	Environmental regulation	10	0.016	0.007	0.020	0.020*	0.034*
1	31	Environmental funding activities	9	0.049	0.047	0.046	0.020*	0.012*
1	89	Sustainability judgment and oil company	9	0.119	0.047	0.195	0.027*	0.103
1	24	The lawsuit case of Chevron	13	-0.033	-0.042	0.048	0.033*	0.029*

1	92	Environmental trading	9	-0.061	-0.035	0.114	0.055†	0.149
1	114	NA	9	-0.028	-0.019	0.044	0.055†	0.096†
1	26	Medicine experiment and environment	5	0.027	0.034	0.015	0.063†	0.017*
1	105	NA	5	0.068	0.052	0.069	0.063†	0.091†
1	39	Environmental regulation and policy / in New Jersey / Exxon	6	-0.040	-0.048	0.042	0.094†	0.065†
1	48	Environmental scandal and updates / VW case	6	0.036	0.040	0.033	0.094†	0.046*

Note: ***p < 0.001, **p < 0.01, *p < 0.05, † < 0.1 (two-tailed). NA means that the generated event cannot be easily interpreted by researchers. N is the number of observations. Day 1 means the day after the event day.

From view of event effects trend, the following Table 4.5 highlights the events with significant event effect changes between day 0 and 1. The event cluster with index 74 (Monsanto's activities and updates) show a significant difference between day 0 and day 1, where the effect of this cluster on day 0 was negative and it became positive on day 1. The trending and asset activities (index41) show a decreasing trend between day 0 and day 1. The environmental fine and settlement show a positive difference between effect on day 0 and day 1, while the event effects on both days are negative.

Table 4.5 Important events during the period [0, 1]

Event Day(s)	Index	Event	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
(0,1)	59	NA	14	0.011	0.005	0.018	0.030*	0.037*
(0,1)	74	Monsanto's activities and updates	6	0.020	0.013	0.022	0.031*	0.076†
(0,1)	41	Trading and asset activities	10	-0.009	-0.008	0.013	0.049*	0.058†
(0,1)	86	Environmental fine and settlement	7	0.005	0.004	0.006	0.078*	0.096†

Note: ***p < 0.001, **p < 0.01, *p < 0.05, † < 0.1 (two-tailed). NA means that the generated event cannot be easily interpreted by researchers. N is the number of observations.

Table 4.6 Important events during the period [0, 5]

Event Day(s)	Index	Event	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
(0,5)	22	emission accusations – Diesel cheating suit	10	0.008	0.005	0.008	0.004*	0.011*
(0,5)	73	Capital and market activities	12	0.006	0.003	0.009	0.007*	0.033*

(0,5)	59	NA	14	0.012	0.009	0.016	0.020*	0.018*
(0,5)	88	NA	7	-0.019	-0.009	0.027	0.031*	0.102
(0,5)	74	Monsanto's activities and updates	6	0.021	0.019	0.014	0.031*	0.012*
(0,5)	115	Environmental agreement	8	-0.035	-0.022	0.055	0.039*	0.120
(0,5)	111	NA	9	0.021	0.013	0.040	0.039*	0.157
(0,5)	44	Environmental concerns / pollution / oil sands	7	-0.006	-0.008	0.008	0.078†	0.075†
(0,5)	3	Walgreen's activities	12	0.009	0.010	0.018	0.092†	0.130
(0,5)	4	Announcements of Market Estimates	9	-0.007	-0.008	0.009	0.098†	0.058†
(0,5)	114	NA	9	0.022	0.022	0.033	0.098†	0.084†

Note: ***p < 0.001, **p < 0.01, *p < 0.05, † < 0.1 (two-tailed). NA means that the generated event cannot be easily interpreted by researchers. N is the number of observations. [0, 5] indicates the period between day 0 (event day) and day 5 (the fifth day after the event day).

The event effects during the period between day 0 (the event day) and day 10 (the tenth day after the event day) indicate whether the event has an effect amplified. The following Table 4.7 show the events with significant effects during the period of Days (0, 10). To measure the importance of the events, we ranked the events based on the significance of AR Median, which is a general measurement of events' impact. The activities related to Keystones lead to a positive and significant effect on market reaction to the involved firms (AR Mean = 0.015; $p < 0.01$; AR Median = 0.017; $p_{WSR} < 0.01$). The updates about emission accusations of diesel cheating suit show a positive impact on market reaction to the involved firms (AR Mean = 0.012; $p < 0.05$; AR Median = 0.009; $p_{WSR} < 0.05$). The M&A activities related to Walgreens and Rite aid indicate a negative impact on firms' market performance (AR Mean = -0.019; $p < 0.01$; AR Median = -0.021; $p_{WSR} < 0.05$). The environmental investigation activities on oil pipeline show a negative impact on market reaction (AR Mean = -0.012; $p < 0.05$; AR Median = -0.008; $p_{WSR} < 0.05$).

Table 4.7 Important events during Days [0, 10]

Event Day(s)	Index	Event	N	Mean	Median	Stand deviation	WSR p-value	t-test p-Value
(0,10)	109	Events related to Keystone	9	0.015	0.017	0.011	0.004**	0.002**
(0,10)	22	Emission accusations – Diesel cheating suit	10	0.012	0.009	0.012	0.010*	0.014*

(0,10)	23	M&A activities of Walgreens and Rite Aid	11	-0.019	-0.021	0.018	0.014*	0.006**
(0,10)	20	Environmental investigation on oil pipeline / In Canada	16	-0.012	-0.008	0.020	0.034*	0.032*
(0,10)	74	Monsanto's activities and updates	6	0.023	0.025	0.018	0.063†	0.024*
(0,10)	12	Environmental incident – Oil spill	10	0.076	0.023	0.161	0.084†	0.171

4.4.2. Notable Events with Continuous Effects

Further, we identified multiple events with continuous effects during the event window. Among the 120 events recognized by the model, our results show that 13 events have significant and continuous AR on firms' market performance (index = 17, 19, 25, 27, 32, 39, 40, 47, 53, 60, 63, 78 and 119) based on the five years data of Thomson Reuters news. The topics of the events were interpreted based on the keywords. The results show the market has been concerning the following sustainability events: Activities related to Brazil Mining (Negative), Sustainability in Australia (Negative), Lawsuit case of Chevron (Negative), Activities of Medicine Experiment and Environment (Positive), Environmental funding activities (Positive), Environmental regulation (Positive), Environmental regulation and policy in New Jersey (Negative), Approval and Support (Positive), Refinery glitches and maintenance (positive), Environmental projects initialization and challenges (Positive), activities related to plants (Positive).

The event cluster with index 17 (Brazil Mining) was found a continuous negative market reaction on the event days between day 0 to day 5, respectively. Specifically, on day 0, it was found a negative and significant effect (AR Mean = -0.019; p_t-test < 0.05; AR Median = -0.019; p_WSR <0.05). The trend of significant median continuous over the remaining days (p_WSR < 0.05), although the AR Means show marginal effects (0.1 < p_t-test < 0.3). The effect does not show an increasing trend as the effect difference over the period from day 0 to day 5 and day 0 to day 10 are not significant (p_WSR > 0.1; p_t-test > 0.1).

Table 4.8 Event study results of cluster 17

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	20	-0.019	-0.019	0.034	0.017*	0.024*
1	20	-0.021	-0.018	0.038	0.007*	0.020*
2	20	-0.016	-0.014	0.048	0.021*	0.160
3	20	-0.016	-0.018	0.047	0.033*	0.138
4	20	-0.014	-0.018	0.058	0.033*	0.289
5	20	-0.016	-0.016	0.050	0.036*	0.162
(0,1)	20	-0.002	-0.001	0.008	0.261	0.197
(0,5)	20	0.003	-0.001	0.021	0.985	0.557

The second event cluster which was found a significant effect is event cluster with index 19. Through researchers' interpretation, it is a cluster related to Sustainability events in Australia. Shown in Table 4.9, it was found a continuous negative impact on the market reaction. A negative and significant event effect was found on the event day (day 0) (AR Mean = -0.065; $p < 0.05$; AR Median = -0.047; p_WSR < 0.05). On the following days, the negative effect continuous on the involved market performance (p_WSR < 0.05; $p < 0.05$). The event effects did not show a significant difference on different event days.

Table 4.9 Event study results of cluster 19

Event Day(s)	N	Mean	Median	Stand deviation	p-Value (WSR)	p-Value (t-test)
0	12	-0.065	-0.047	0.089	0.016*	0.028*
1	12	-0.065	-0.039	0.088	0.012*	0.027*
2	12	-0.066	-0.045	0.092	0.016*	0.029*
3	12	-0.072	-0.045	0.100	0.009**	0.031*
4	12	-0.065	-0.043	0.094	0.016*	0.035*
5	12	-0.074	-0.052	0.104	0.009**	0.031*
(0,1)	12	0.000	0.001	0.019	0.569	0.941
(0,5)	12	-0.009	-0.005	0.023	0.266	0.205

(0,10)	12	-0.003	-0.004	0.022	0.301	0.645

The third cluster that found a significant effect is event cluster with index 25. The cluster was related to the lawsuit case of Chevron. Based on the statistical results, as shown in the following Table 4.10, negative effects were found on the five event days respectively (p_WSR < 0.05; p <0.05), suggesting a continuous negative influence on firms' market performance. The trend of effects is stable and no significant changes among these effects.

Table 4.10 Event study results of cluster 25

Event Day(s)	N	Mean	Median	Stand deviation	p-Value (WSR)	p-Value (t-test)
0	13	-0.033	-0.036	0.049	0.033*	0.032*
1	13	-0.033	-0.042	0.048	0.033*	0.029*
2	13	-0.040	-0.046	0.046	0.008**	0.008**
3	13	-0.049	-0.046	0.047	0.005**	0.003**
4	13	-0.046	-0.046	0.049	0.010*	0.005**
5	13	-0.043	-0.044	0.052	0.017*	0.011*
(0,1)	13	0.000	-0.004	0.010	0.635	0.978
(0,5)	13	-0.010	-0.008	0.031	0.340	0.245
(0,10)	13	-0.002	0.000	0.040	1.000	0.879

The fourth notable event cluster is cluster 27. Based on the event interpretation, this event cluster is related to activities of medicine experiment and environment. As shown in Table 4.11, the statistical results indicate that positive effects on the four event days, though the event effect on the day 5 is insignificant: day 0 (AR Mean = 0.026; p < 0.1; AR Median = 0.034; p_WSR < 0.1); day 1 (AR Mean = 0.027; p < 0.05; AR Median = 0.034; p_WSR < 0.1); day 2 (AR Mean = 0.032; p < 0.05; AR Median = 0.034; p_WSR < 0.1); day 3 (AR Mean = 0.034; p < 0.01; AR Median = 0.010; p_WSR < 0.1); day 4 (AR Mean = 0.037; p < 0.05; AR Median = 0.032; p_WSR <

0.1). There is no significant change among different event days (p_t-test > 0.1; p_WSR > 0.1).

Table 4.11 Event study results of cluster 27

Event Day(s)	N	Mean	Median	Stand deviation	p-Value (WSR)	p-Value (t-test)
0	5	0.026	0.018	0.024	0.063†	0.072†
1	5	0.027	0.034	0.015	0.063†	0.017*
2	5	0.032	0.034	0.010	0.063†	0.002**
3	5	0.034	0.032	0.016	0.063†	0.009**
4	5	0.037	0.031	0.020	0.063†	0.015*
5	5	0.030	0.028	0.033	0.125	0.116
(0,1)	5	0.001	0.003	0.017	0.625	0.935
(0,5)	5	0.004	0.015	0.025	0.813	0.750
(0,10)	5	0.032	0.032	0.071	0.625	0.370

Fifth, event cluster 32 is related to Environmental funding activities. The statistical results are shown in the following Table 4.12. On day 0, it was found a positive event effect (AR Mean = 0.048; p < 0.05; AR Median = 0.046; p_WSR < 0.05). The positive effects were continuous and positive event effects found on the following day 1 to day 5, respectively (all p_WSR < 0.05; p_t-test <0.05).

Table 4.12 Event study results of cluster 32

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.048	0.046	0.047	0.020*	0.016*
1	9	0.049	0.047	0.046	0.020*	0.012*
2	9	0.048	0.035	0.051	0.020*	0.024*
3	9	0.054	0.058	0.049	0.020*	0.011*
4	9	0.048	0.037	0.050	0.020*	0.022*
5	9	0.049	0.032	0.055	0.020*	0.028*
(0,1)	9	0.001	0.000	0.009	0.820	0.708
(0,5)	9	0.001	-0.006	0.017	1.000	0.891
(0,10)	9	0.011	0.014	0.021	0.203	0.158

The sixth notable event cluster is Environmental regulation (index 39). As shown in the following Table 4.13, the effects start from day 0 (AR Mean = 0.015; AR Median=0.010; p_WSR < 0.05; p_t-test <0.05) and continuous until day 5 (AR Mean = 0.019; AR Median = 0.015; p_WSR < 0.05; p_t-test < 0.1).

Table 4.13 Event study results of cluster 39

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.015	0.010	0.017	0.014*	0.019*
1	10	0.016	0.007	0.020	0.020*	0.034*
2	10	0.014	0.006	0.023	0.037*	0.095†
3	10	0.017	0.010	0.023	0.037*	0.046*
4	10	0.019	0.012	0.027	0.037*	0.054†
5	10	0.019	0.015	0.029	0.037*	0.062†
(0,1)	10	0.001	0.000	0.005	0.846	0.508
(0,5)	10	0.004	0.000	0.016	0.625	0.384
(0,10)	10	0.008	-0.003	0.023	1.000	0.276

Table 4.14 Event study results of cluster 40

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	-0.042	-0.057	0.044	0.156	0.068†
1	6	-0.040	-0.048	0.042	0.094†	0.065†
2	6	-0.042	-0.060	0.049	0.094†	0.089†
3	6	-0.032	-0.049	0.046	0.156	0.144
4	6	-0.041	-0.051	0.050	0.094†	0.105
5	6	-0.044	-0.060	0.048	0.094†	0.077†
(0,1)	6	0.002	-0.001	0.009	1.000	0.558
(0,5)	6	-0.001	0.002	0.017	1.000	0.848
(0,10)	6	0.000	0.000	0.009	1.000	0.900

The seventh event cluster (index = 40) was interpreted as Environmental regulation and policy / in New Jersey. It shows a negative effect over the period from day 0 to day 5. The eighth, ninth, eleventh, and twelfth notable events are related to approval and support (index = 47), Refinery glitches and maintenance (index = 48), Environmental projects initialization and challenges (index = 63), and activities related to plants respectively (index78), while the tenth (index = 60) and thirteenth (index =

119) events are not able to be interpreted. The event cluster related to approval and support (index = 18) positively impacts companies' market performance.

Table 4.15 Event study results of cluster 47

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	18	0.031	0.024	0.046	0.007*	0.011*
1	18	0.035	0.021	0.052	0.002*	0.011*
2	18	0.036	0.024	0.053	0.004*	0.010*
3	18	0.037	0.030	0.051	0.001*	0.008*
4	18	0.034	0.020	0.054	0.003*	0.015*
5	18	0.031	0.017	0.057	0.016*	0.031*
(0,1)	18	0.004	0.002	0.017	0.325	0.345
(0,5)	18	0.000	0.012	0.036	0.580	0.964
(0,10)	18	-0.006	0.016	0.061	0.702	0.659

Table 4.16 Event study results of cluster 53

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	19	0.021	0.026	0.024	0.002**	0.001**
1	19	0.019	0.028	0.027	0.008**	0.007**
2	19	0.020	0.022	0.027	0.002**	0.004**
3	19	0.017	0.022	0.030	0.020*	0.029*
4	19	0.020	0.028	0.032	0.032*	0.013*
5	19	0.019	0.033	0.038	0.029*	0.044*
(0,1)	19	-0.002	-0.002	0.009	0.490	0.371
(0,5)	19	-0.002	-0.001	0.026	0.984	0.736
(0,10)	19	0.001	0.000	0.026	0.768	0.891

Table 4.17 Event study results of cluster 60

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	14	0.010	0.006	0.019	0.119	0.091†
1	14	0.021	0.016	0.019	0.001**	0.001**
2	14	0.017	0.011	0.018	0.004**	0.004**
3	14	0.019	0.012	0.023	0.007**	0.009**
4	14	0.019	0.012	0.020	0.001**	0.003**
5	14	0.021	0.020	0.019	0.001**	0.001**
(0,1)	14	0.011	0.005	0.018	0.030*	0.037*
(0,5)	14	0.012	0.009	0.016	0.020*	0.018*
(0,10)	14	0.010	0.005	0.025	0.194	0.146

Table 4.18 Event study results of cluster 63

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.009	0.005	0.014	0.021*	0.044*
1	12	0.009	0.005	0.012	0.016*	0.029*
2	12	0.010	0.008	0.013	0.016*	0.019*
3	12	0.012	0.010	0.013	0.002*	0.011*
4	12	0.012	0.010	0.013	0.007*	0.010*
5	12	0.013	0.010	0.015	0.003*	0.012*
(0,1)	12	0.000	0.001	0.005	0.910	0.972
(0,5)	12	0.004	0.007	0.010	0.129	0.165

Table 4.19 Event study results of cluster 78

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	0.028	0.033	0.024	0.250	0.107
1	4	0.034	0.037	0.023	0.125	0.058†
2	4	0.032	0.032	0.011	0.125	0.010*
3	4	0.025	0.027	0.012	0.125	0.027*
4	4	0.034	0.029	0.015	0.125	0.019*
5	4	0.037	0.035	0.015	0.125	0.015*
(0,1)	4	0.007	0.007	0.006	0.250	0.107
(0,5)	4	0.010	-0.005	0.036	0.875	0.627
(0,10)	4	0.018	0.007	0.041	0.625	0.446

Table 4.20 Event study results of cluster 119

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	-0.018	-0.018	0.002	0.250	0.005**
1	3	-0.020	-0.021	0.003	0.250	0.008**
2	3	-0.020	-0.023	0.004	0.250	0.014*
3	3	-0.022	-0.025	0.006	0.250	0.022**
4	3	-0.029	-0.031	0.006	0.250	0.015*
5	3	-0.022	-0.025	0.007	0.250	0.030*
(0,1)	3	-0.002	-0.002	0.001	0.250	0.066†
(0,5)	3	-0.005	-0.007	0.005	0.500	0.227
(0,10)	3	-0.006	-0.012	0.013	0.500	0.485

Robustness checks. We conducted additional checks to ensure the robustness of results. First, we implemented both parametric and non-parametric tests on both median and mean for evaluating the AR. The t-test is a well-adopted statistical indicator for determining whether there is a significant difference of AR between the sample group and reference group. However, in some situations, such as plausible extreme data points or small sample sizes, the results of t-test might be vulnerable to bias. To address this issue, consistent with existing literature (Lo et al., 2014), we performed both WSR and t-test, where the results of WSR are mainly focused and the results of t-test provides additional support. Thus, we consider an event to have an AR when it has significant WSR statistics based on the median, and the t-test is considered as additional support based on the mean. Also, we assess AR over multiple event days to measure the consistent impact of events. Specifically, AR is measured based on expected returns based on reference market estimates, and empirical results show that event-induced AR is significant both at the time of the event and over multiple days after the event. These measures ensure the validity of event-induced significant effects. In addition, tests on the event period (i.e., [0, 1], [0, 5], [0, 10]) indicate the trend of the event, whether an amplification or a mitigation effect is evident.

4.5. DISCUSSION AND CONCLUSION

While there has been streams of research studying sustainability events, the impact of emerging events and their importance are still under-researched. Previous studies have suggested several suitability events can trigger significant market reactions, such as initialization of sustainable program (Ba et al., 2013; Jacobs, 2014), awards and incidents (Klassen & McLaughlin, 1996; Lo et al., 2018), sustainability disclosure and reporting (Grewal et al., 2019; Xu et al., 2022; Yang et al., 2021). Nevertheless, we reveal that more ESEs have been leading to a market reaction. Based on the developed DDEA and empirical results, our study recognized the most important ESEs and events with sequential effects for each critical day. By examining the impact of events and ranking their importance, we provide managers with insights on which ESEs need more attention. In the following, we discuss the theoretical and managerial implications of this study.

4.5.1. Managerial Implications

This study has several contributions to practice. First, this study helps sustainability managers enhance their understanding of ESEs and their impact on the stock market. Our findings reveal that investors are sensitive and react to a series of ESEs. Based on the empirical results, our findings on ESEs alert companies to consider these important events, which can be helpful for managers to focus on them at an early stage. When these sustainability events occur, the market are likely to react positively (e.g., Environmental funding) or negatively (e.g., Lawsuit case of Chevron) to them. Managers need to proactively prepare for these effects when their companies or supply chain partners have similar business. Managers should create an “ESE portfolio” to proactively allocate their resources and develop rapid strategies. From a buyer's perspective, when a negative new event occurs, managers should be aware of the company involved and the nature of this event. Companies should consider supply chain risks that may affect their business operations (such as default risk, late delivery and environmental penalty risk) and consider alternative supply chain partners in advance. On the other hand, when selecting suppliers, companies may consider companies with more positive ESEs than negative ones. From the supplier's perspective, companies also need to consider risks, as the buyer may be involved in negative sustainability events and fail to fulfill the contract. Overall, this study offers a new way for managers to reduce supply chain risk and explore opportunities.

Second, our findings suggest that managers' attention to events should have a more precise granularity. While previous literature has made efforts to identify sustainability events, this study reveals that the impact of events on each company may be uneven. Specifically, our findings suggest that managers consider the impact of ESEs to be "local" rather than "global". The same event may have opposite effects on the different groups of companies involved. For example, the model recognized a significant and positive effect from an event related to environmental regulation. This event involved five companies in a three-year period. However, another recognized event cluster related to environmental regulation and settlement involving the company of Exxon shows a significant and negative effect. This result indicate that events may affect only the companies involved, not the entire population. A refined strategy can provide managers with a better position to face the uncertainty of opportunities and risks in a constantly changing market than a general consideration of events.

In addition, our empirical evidence suggests that ESEs may not only come from completely new event categories, but also from some known activities. The findings indicate that several sustainability events (e.g., lawsuits, glitches, funding, approval, and program initialization) are still trigging the market's reaction. Therefore, apart from discovering new events, these important and ESEs should not be neglected by managers as they are concerned by investors.

4.5.2. Theoretical Implications

This study offers several theoretical contributions. First, our study fills the gap in studies on ESEs. Despite the sustainable events have been an important topic for event studies for conducting research, it lacks knowledge on ESEs that are easily be overlooked by researchers. This study fills this gap by examining the ESEs and highlight the most important ones. To the best of our knowledge, the present study is among the first research to address this research gap in event study literature.

Second, this study shed light on event study through conducting the first large-scale data-driven study for sustainability events. Previous studies rely on hypothesis driven research design for developing theories, however the data-driven event study is more practical as it handles multiple events and provide straightforward insights for management practices. Based on a data-driven event study design, this study examines a series of ESEs rather than a single event. The results of the empirical study suggest that a variety of ESEs add to the literature and theories. To the best of our knowledge, this study is the first study proposing and conducting data-driven event analysis.

In addition, our study highlights the importance of granularity for event study research. We suggest researchers and managers should also consider events with “local effects.” Previous literature on sustainability events generally considers an event with general “global effects”, that means the event should be able to signal the same to the firms in the whole market or industry. Conflict findings are found in the literature for similar events (Ba et al., 2013; Dam & Petkova, 2014; Jacobs, 2014). In this study, our results show that not all events have general effects – some events may only negatively affect a firm's stock price while the event effects on other involved firms are reversed. For example, one event cluster is interpreted as refinery glitches and maintenance, which is a generally negative event. However, we find that only one firm's market reaction is negative, and all other involved firms receive positive market reactions. This evidence indicates an important finding that when the market may react reversely to different companies involved in the same event. Indeed, when a firm is facing glitches, and their short-term productivity may reduce, the investors will consider other firms in the industry to gain more revenues.

4.5.3. Limitations and Future Research

There are limitations to our study. First, in the scope of this work, we only design and conduct event studies focusing on the sustainability events. Though sustainability is one important topic for research and practice, more unexpected events exist for different topics related to firms' operations and production. Future research may extend the framework of this study and explore the unexpected from on other important topics. Second, in this study, we focus on exploring the ESEs for helping managers to manage the unexpected. However, the event effects (i.e., AR) may also be affected by various factors. Thus, future research could extend *DDEA* and integrate the regression models in the data-driven model. By doing so, research may regress the estimated AR with multiple variables to see *what* the additional conditions affects the outcomes. Third, for estimations of expected returns, this study focusses on the results of market model, which is the widely adopted measurement in the event study literature for efficient analyses. Future studies may consider various alternative models of expected return estimations, such as Fama-French three factors, four factors and five factors models, market adjusted models and other estimation models to provide additional evaluations of the ESEs. Third, we focus on the ESEs which have few samples. Though the ESEs can provide insights for managers in their strategies, this make the results cannot be considered as theory development directly. Therefore, future studies may revisit the highlighted events and conduct hypothesis-driven event studies when more data are available and sample size increased. Lastly, this study is a combination of methodology innovation and empirical findings. Yet, as the limitation of the data available, in this study, we are not able to analyze the effects of some most famous unexpected event, such as Covid-19. Future research is recommended to extend this study and provide more detailed insights by considering data that include the news related to Covid-19 and other most recent unexpected events.

5. CHAPTER 5: CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

To sum up, this thesis applies econometric models and AI (NLP and machine learning) models to address three important aspects of sustainability events: sustainability reporting and company performance, the *EventMining* method development based on company news and NLP techniques, and the impact of ESEs on market reactions. Sustainability is becoming an increasingly important issue in corporate strategies. Recent research has examined the impact of sustainability reporting on corporate profitability, which is so far a voluntary disclosure that is made in addition to the mandatory sustainability disclosures (Yang et al., 2021). However, little is known about how internal stakeholders, such as operational employees and senior management, use sustainability reports to improve operational efficiency. Taken together, Study 1 examined the impact of sustainability reporting on profitability and operational efficiency. Also, the role of observability was examined using the proxies *first-time reporting*, *reporting frequency*, and *media exposure*. The findings suggest that GRI reporting has a time-lagged positive impact not only on profitability (Return on Assets (ROA) and *Tobin's q* and market value) but also on operational efficiency (*labor productivity* and COGS/*Sales*). The regression results show that these proxies can improve profitability in terms of the return on abnormal assets and operational efficiency in terms of labor productivity through a "reverse" signaling effect. However, these proxies fail to improve the market value and COGS/*Sales*, suggesting some weaknesses in the signaling effect. The findings suggest that company executives should pay more attention to internal stakeholders (employees) and sustainable operations when investing in GRI reporting. This study fills the research gap related to SR in driving financial performance and productivity within the integrated framework of stakeholder theory and signaling theory. This study highlights that SR can be used as an integral part of sustainable operations to improve operations and production, not just to support PR activities. The findings underscore the significance of adopting stringent sustainability disclosure standards.

Event studies are the most popular method for gaining insights into the relationship between events and company performance (Ding et al., 2018). However, work on the development of advanced methods to address manual event identification is still scarce. This gap is limiting researchers and managers from gaining a deeper understanding of sustainability events. Recent developments in NLP and machine learning have enabled replacing some of the manual work of researchers in this area. Therefore, the second study proposed *EventMining*, which is an NLP-based event identification method to replace the manual work previously done by researchers and managers. The proposed *EventMining* approach uses company news to identify multiple event cases, with less intervention needed by researchers, which provides an avenue for carrying out large-scale event research. This study is among the first to advance event research methods using NLP and machine learning techniques.

The increasingly competitive markets require managers to make decisions and formulate strategies quickly and to keep an eye on emerging events (Forbes, 2019). Building on the shoulders of Study 1 and Study 2, we sought a greater substantive contribution to the study of sustainability events by focusing on Emerging Sustainability Events (ESEs). In this regard, the third study aimed to design a data-driven event analysis approach based on NLP-based event recognition and then examined the ESEs to discover the most important ones based on quantitative empirical analysis. This study is among the first to investigate emerging sustainability events using a large-scale data-driven event study design. Thus, this study applied and extended the NLP-based event recognition methodology and applied it to reveal insights into the focus of emerging events.

This dissertation makes the following main contributions to the field. First, the dissertation contributes to the sustainability literature and practice by highlighting the significance of conducting voluntary sustainability reporting for manufacturing firms. Information asymmetry of the sustainability information between firms' top managers and broader stakeholders has long existed. However, companies can utilize sustainability reporting as an effective approach to signal to their stakeholders that the impact of SR on the firms' market performance is positive and significant. As a reverse effect, firms can also receive operational enhancements from their employees by addressing this information asymmetry among different parties and by unifying their sustainability goals. As such, this study therefore provides insights to managers to address the question of "whether they should talk more about their sustainability practices" and to avoid the managers falling in to a lose–lose dilemma of closing the door on transparency. The *EventMining* proposed in Study 2 offers a brand-new way for researchers and managers to understand events that happen in the market. To the best of our knowledge, the proposed method is among the first to advance the event identification method using artificial intelligence (NLP and machine learning models). By utilizing this method, managers and researchers can achieve the goals of analyzing the market news efficiently and comprehensively and event cases can be generated for gaining managerial insights. As such, Study 2 contributes to both event study research and AI research by establishing a new approach for an important task: NLP-based event identification. The 120 sustainability event cases identified are considered ESEs as they are important sustainability events but the observations are not large. In study 3, we quantitively examined the impact of the event cases and highlighted the most important ESEs by ranking their effects using a data-driven event analysis design. As a novel goal addressed by a novel method, Study 3 has implications for both the sustainability literature and the methodology literature by revealing the important ESEs. Managers are able to focus on these ESEs to ensure they develop proactive strategies and for effective planning. Overall, this dissertation provides implications for sustainable operations management and event study methodology through a design approach comprising events study, *EventMining*, and the data-driven event analysis of ESEs, which reflects the evolution of event study research in the AI-enabled era.

6. APPENDICES

6.1. Appendix I. Summary of Related Literature on Sustainability Reporting

Author(s)	Sample	IV(s)	DV(s)	Moderator/ Mediator	Theory	Key Findings
Panel A. DV = Profitability or financial (ROA, ROS)						
(Ching et al., 2017)	Cross-industry firms listed on corporate sustainability index (2008-14)	Sustainability reporting quality	Corporate financial performance	--	--	• *No clear consensus* on relationship between sustainability performance and financial performance.
(Arevalo & Aravind, 2017)	Cross-industry survey of Spanish firms that participate in UN GC (2009-11)	Firm performance, access to business networks, organizational resources, access to CSR networks	Economic benefit, reputational benefits	--	Strategic CSR theory, Network theory, Resource-based view theory	• Firm performance, access to business networks, resources, and access to CSR networks are positively related to the economic and reputational benefits through participating in the GC.
(Buallay, 2019)	ESG disclosures by 235 banks (2007-16)	Environmental disclosure, corporate social responsibility disclosure, corporate governance disclosure (ESG scores)	ROA, ROE	--	Stakeholder theory, instrumental theory, anticipation theory	• ESG disclosure positively affects ROA and ROE. However, the results of the subcategory scores (i.e., disclosures on CSR and corporate governance) show *negative* effects on ROA and ROE.
(Yang et al., 2021)	Cross-industry GRI reporting by 122 Chinese firms (2008-16)	GRI reporting	ROA, ROS	Central political ties, local political ties, internationali-zation level	Signaling environment, signaling strength	• GRI reporting significantly affects profitability of firms. • Local political ties positively moderate the relationships, where the internationalization level of a firm impedes the effects. • Central political ties have no effect on the GRI-profitability relationship.
(Swift et al., 2019)	1180 firms form disclosures under Dodd-Frank Act.	Disclosure - visibility into mineral conflict supply chains	ROA	-	Knowledge	• High visibility into mineral conflict supply chain positively linked to ROA
Panel B. DV = Market gains (market share, revenue, share price, *Tobin's q*)						

(Verbeeten et al., 2016)	Cross-industry GRI German companies, 4 years data	Voluntarily disclosed CSR social information, voluntarily disclosed environmental CSR information	Firm value (share price, return per share)	--	Stakeholder theory, legitimacy theory	• Voluntarily disclosed social information positively affects firm value. • However, the effect of voluntarily disclosed environmental information is *not significant*.
(Loh et al., 2017)	Cross-industry 502 Singaporean firms listed on the SGX mainboard	Sustainability adoption	Market value	--	Agency theory, signaling theory, and legitimacy theory.	• Sustainability reporting adoption is positively related to the market value.
(Cuadrado-Ballesteros et al., 2016)	Cross-industry 1260 international non-financial listed firms (2007-2014)	Financial reporting quality, social reporting quality	Price-earnings-growth	Information asymmetry	--	• High-quality financial and social disclosure reduces the cost of capital, mediated by the reduction of information asymmetry.
(Lee & Maxfield, 2015)	Cross-industry GRI 126 US firms (2007 to 2008)	Reporting activities	Tobin's Q	--	Stakeholder theory, institutional theory, agency theory	• GRI reporting has positive effects on Tobin's q performance, where traditional CSR reporting shows non-significant effects.
(Buallay, 2019)	ESG disclosures by 235 banks (2007-16)	Environmental disclosure, corporate social responsibility disclosure, corporate governance disclosure (ESG scores)	Tobin's Q	--	Stakeholder theory, instrumental theory, anticipation theory	• ESG disclosure positively affects Tobin's q. • However, the results of the subcategory scores (i.e., disclosures on CSR and corporate governance) show *negative* effects on Tobin's q.
(Swift et al., 2019)	1180 firms form disclosures under Dodd-Frank Act.	Disclosure - visibility into mineral conflict supply chains	Stock market, sales	-	Knowledge	• High visibility into mineral conflict supply chain positively linked to stock market and sales.
Panel C. DV = Operational efficiency (*COGS/Sales* and *labor productivity*)						
--	--	--	--	-	--	--
Panel D. DV = ESG performance						
(Bernard et al., 2015)	Cross-industry (qualitative)	GRI reporting	CO_2 emission	--	--	• Comparing the reporting and non-reporting companies, only companies in a specific industry (utilities) show a dramatic decrease in emissions intensity.

(Belkhir et al., 2017)	Cross-industry 40 firms with GRI & 24 without GRI reporting	GRI reporting	CO_2 emission reduction	--	--	• The accumulated difference of CO_2 emissions between the GRI-reporting and non-GRI reporting groups are *negligible*.
(Bae et al., 2018)	Cross-industry in Bangladesh, India, and Pakistan (2009-16)	Foreign shareholding, institutional shareholding, director shareholding, outside directors, board size	Total sustainability disclosure score	--	Signaling theory, agency theory,	• Identified several sources of shareholder pressure that have significant effects on sustainability disclosure.
(Lee & Maxfield, 2015)	Cross-industry GRI 126 US firms (2007 to 2008)	Reporting activities	ESG performance	--	Stakeholder theory, Institutional theory, Agency theory	• GRI reporting has positive effects on ESG performance, where traditional CSR reporting shows non-significant effects.
Panel E. Stakeholder pressures						
(Fernandez-Feijoo et al., 2014)	Cross-industry GRI (2008-10)	Pressures: environmental sensitive industry, consumer proximity industry, pressure from investors, pressure from employees	Quality & transparency of SR	--	Stakeholder theory	• Pressures from different groups improve the quality of transparency of sustainability reports.

6.2. Appendix II: Correlation Matrix and Descriptive Analysis

Table A1. Descriptive Statistics and Correlation Matrix for ROA

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abnormal ROA	1.000						
(2) Sustainability related media exposure	0.028	1.000					
(3) First-time GRI Reporting	0.020	0.015	1.000				
(4) Reporting frequency	0.005	-0.003	-0.864*	1.000			
(5) Sample's ROA	0.037	-0.083*	-0.071*	0.056	1.000		
(6) Industry's ROA	-0.078*	0.387*	0.046	-0.051	-0.104*	1.000	
(7) log (firm size)	-0.119*	-0.177*	-0.230*	0.217*	0.080*	-0.032	1.000
Mean	.011	-2.251	.206	.655	.069	-.179	9.416
SD	.043	.629	.405	.386	.078	.229	1.396

Note: *** *p<0.01, ** p<0.05, * p<0.1* (two-tailed)

Table A2. Descriptive Statistics and Correlation Matrix for LP

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abnormal LP	1.000						
(2) Sustainability related media exposure	-0.069*	1.000					
(3) First-time GRI Reporting	-0.029	0.008	1.000				
(4) Reporting frequency	0.059	0.008	-0.864*	1.000			
(5) Sample's ROA	-0.024	-0.124*	-0.059*	0.040	1.000		
(6) Industry's ROA	-0.061*	0.391*	0.040	-0.048	-0.122*	1.000	
(7) log (firm size)	0.056	-0.184*	-0.218*	0.199*	0.141*	-0.040	1.000
Mean	8.349	-2.25	.205	.656	.067	-.179	9.373

SD	54.334	.634	.404	.386	.084	.23	1.426

Note: *** *p<0.01*, ** *p<0.05*, * *p<0.1* (two-tailed)

Table A3 Descriptive Statistics and Correlations Matrix of COGS/Sales model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abnormal COGS/sales	1.00						
(2) Sustainability related media exposure	-0.167*	1.00					
(3) First-time GRI Reporting	-0.05	0.00	1.00				
(4) Reporting frequency	0.03	0.01	-0.864*	1.00			
(5) Sample's ROA	0.093*	-0.116*	-0.05	0.04	1.00		
(6) Industry's ROA	-0.01	0.392*	0.04	-0.05	-0.116*	1.00	
(7) log (firm size)	0.168*	-0.192*	-0.217*	0.198*	0.151*	-0.05	
Mean	-0.03	0.20	0.07	9.40	-2.26	0.66	-0.18
SD	0.15	0.40	0.08	1.42	0.63	0.39	0.23

Note: *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table A4 Descriptive Statistics and Correlations Matrix of Market Value model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abnormal Tobin's q	1						
(2) Sustainability related media exposure	-0.088*	1					
(3) First-time GRI Reporting	0.023	0.008	1				
(4) Reporting frequency	-0.024	0.008	-0.864*	1			
(5) Sample's ROA	0.01	-0.124*	-0.059*	0.04	1		
(6) Industry's ROA	-0.105*	0.391*	0.04	-0.048	-0.122*	1	
(7) log (firm size)	-0.063*	-0.184*	-0.218*	0.199*	0.141*	-0.04	1
Mean (MV)	425.169	-2.25	.205	.656	.067	-.179	9.373
SD (MV)	19113.681	.634	.404	.386	.084	.23	1.426

Note: *** p<0.01, ** p<0.05, * p<0.1 (two-tailed).

Table A5 Descriptive Statistics and Correlation Matrix of Tobin's q model

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Abnormal market value	1.000						
(2) Sustainability related media exposure	-0.088*	1.000					
(3) First-time GRI Reporting	0.023	0.008	1.00				
(4) Reporting frequency	-0.024	0.008	-0.864*	1.000			
(5) Sample's ROA	0.010	-0.124*	-0.059*	0.040	1.000		
(6) Industry's ROA	-0.105*	0.391*	0.040	-0.048	-0.122*	1.000	
(7) log (firm size)	-0.063*	-0.184*	-0.218*	0.199*	0.141*	-0.040	1.000

Mean (MV)	425.169	-2.25	.205	.656	.067	-.179	9.373
SD (MV)	19113.681	.634	.404	.386	.084	.23	1.426

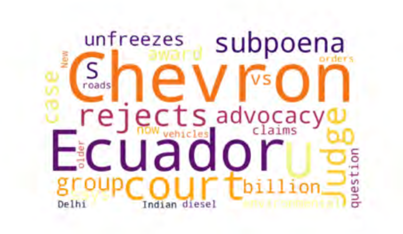
Note: *** p<0.01, ** p<0.05, * p<0.1 (two-tailed)

6.3. Appendix III: Tag Description

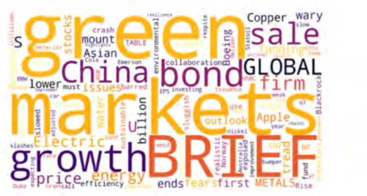
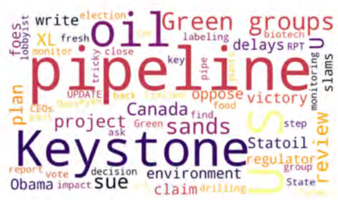
Number	Tag	Description
1.	CC	Coordinating conjunction
2.	CD	Cardinal number
3.	DT	Determiner
4.	EX	Existential *there*
5.	FW	Foreign word
6.	IN	Preposition or subordinating conjunction
7.	JJ	Adjective
8.	JJR	Adjective, comparative
9.	JJS	Adjective, superlative
10.	LS	List item marker
11.	MD	Modal
12.	NN	Noun, singular or mass
13.	NNS	Noun, plural
14.	NNP	Proper noun, singular
15.	NNPS	Proper noun, plural
16.	PDT	Predeterminer
17.	POS	Possessive ending
18.	PRP	Personal pronoun

19.	PRP$	Possessive pronoun
20.	RB	Adverb
21.	RBR	Adverb, comparative
22.	RBS	Adverb, superlative
23.	RP	Particle
24.	SYM	Symbol
25.	TO	*to*
26.	UH	Interjection
27.	VB	Verb, base form
28.	VBD	Verb, past tense
29.	VBG	Verb, gerund or present participle
30.	VBN	Verb, past participle
31.	VBP	Verb, non-3rd person singular present
a32.	VBZ	Verb, 3rd person singular present
33.	WDT	Wh-determiner
34.	WP	Wh-pronoun
35.	WP$	Possessive wh-pronoun
36.	WRB	Wh-adverb

6.4. Appendix IV: List of Event Cases

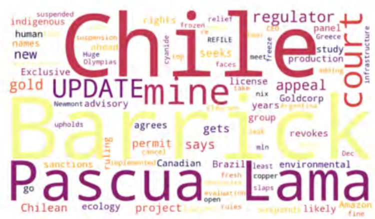
Cluster	**Word Cloud Visualization Keywords for reference**	**Valid Time (year-level) "When"**	**Valid Companies Involved "Who"**	**Valid event cases found "What"**
1		2011, 2014	BP, TRP	*Case 1: Environmental Debate..*
2		2011, 2013, 2016	AMZN, CVX, TM	*Case 2: Environmental lawsuit.*

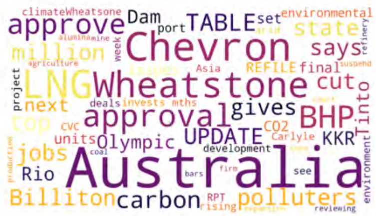
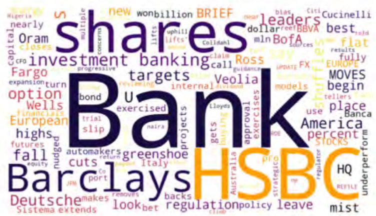
3		2011, 2012	BP, COP, CVX, VLO, XOM	*Case 3: Environmental incident/pollution/maintenance.*
4		2015, 2016, 2017	CVS, KSS, TGT, WBA	*Case 4: Pharmacy retailing activities*
5		2011, 2012, 2013, 2014, 2015	ACN, BAC, BRRY, BCS, ERIC, GEB, MS, SAP, STT	*Case 5: Announcements of Market Estimations.*

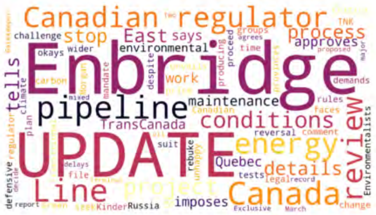
6		2011, 2013, 2014, 2015, 2016, 2017	AA, AAPL, AMZN, BA, BCS, BLK, BP, DUK, EMR, HSBC, KO, MS, STO, TSLA, UN, WMT	*Case 6: Environmental Investment.*
7		2011, 2013, 2014	CVX, ENB, MON, STO, TRP	*Case 7: Environmental Conflicts – Projects, Conflicts, and Government policies.*
8		2012, 2013, 2014, 2015, 2016	BRK.A, F, GM	*Case 8: Green vehicles.* .

9		2012, 2016	BT, EV	*Case 9: Medical* approval in Europe region.
10		2012, 2014, 2015	AEUA, BP	*Case 10: Environmental fine.*
11		2011, 2012, 2013, 2014, 2015, 2016	AMZN, BBL, VALE.P	*Case 11: Environmental activities / in Brazil*

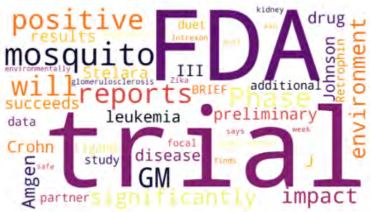
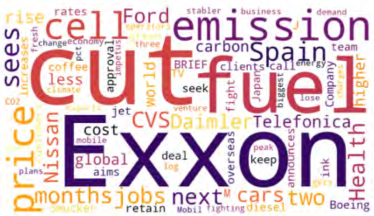
12		2012, 2013, 2014, 2015, 2016, 2017	AMOV, BABA, BCS, C, CHK, CS, DB, FCAU, GS, HSBC, ITUB, IX, MET, MS, NMR, PBR, SCHW, STT, TI, USB, WBA, WFC	*Case 12: Fitch's Rating.*
13		2011, 2012, 2013, 2014, 2015, 2016	AMZN, CEO, COP, XOM	*Case 13: Environmental incident – Oil spill.*
14		2015, 2016	CMI, GM, TM	Case 14: Diesel and electric car

15		2011, 2012, 2016	NAV, TM	Case 15: New collaboration and project on green car
16		2011, 2012, 2013, 2014, 2015, 2016	AAL, BA, BLK, FCX, GEB, HSBC, KO, LMT, NKE, OXY, TMUSP, TRP	Case 16: CEO's attitudes and speaking
17		2013, 2014, 2015, 2016	ABX, AMZN, EGO, GG, NEM	Case 17: Brazil Mining

18		2011, 2013, 2014, 2015, 2016	APPL	Case 18: Apple’ sustainability activities
19		2011, 2012, 2013, 2014, 2015	AA, APA, BBL, CVX, KKR, RIO	Case 19: Sustainability events in Australia
20		2011, 2012, 2013, 2014, 2015, 2016, 2017	BAC, BBVA, BCS, DB, HSBC, LYG, MS, WFC, XOM	Case 20: Banking activities

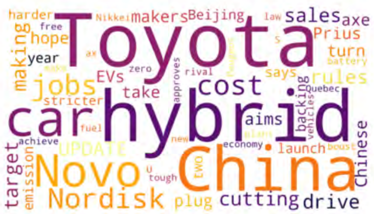
21		2011, 2012, 2014, 2015, 2016, 2017	AGR, BP, ENB, KMI, SNP, TRP	Case 21: Environmental investigation on oil pipeline / In Canada
22		2013, 2014, 2015, 2016 2013, 2015	AMGN, AZN, BMY, GILD, GSK, NICE, SNY TEF, TM	Case 22: Medicine approval in Europe/ Coping Strategies to regulations in Europe
23		2015, 2016, 2017	CMI, FCAU, TM	Case 23: emission accusations – Diesel cheating suit

24		2015, 2016	FRED, KR, RAD, WBA	Case 24: M&A activities of Walgreens and Rite Aid
25		2011, 2012, 2013, 2014	CVX	Case 25: The lawsuit case of Chevron
26		-	-	Case 26: NA

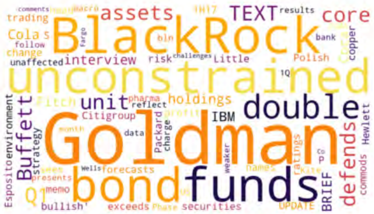
27		2015, 2016	AMGN, JNJ, LGND, XON	Case 27: Medicine experiment and environment
28		2011, 2012, 2013, 2014, 2016	BA, F, SJM, TEF, TM, VOD, XOM	Case 28: Emission reduction
29		2012, 2013, 2014, 2015, 2016	AEUA, MPC, MT	Case 29: Environmental dispute

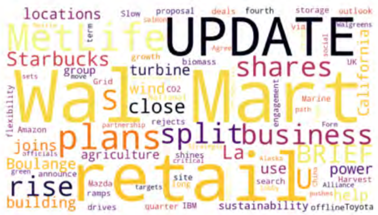
30		2011, 2012, 2015	TSO, XOM	Case 30: Activities related to Exxon refinery
31		2012, 2014, 2016	APPL, COP, CVX, KMI, OXY, TM	Case 31: Environmental project stuck
32		2012, 2013, 2014, 2016	APPL, DISH, HAL, JPM, NKE, STT, TM, TRI, WMT	Case 32: Environmental funding activities

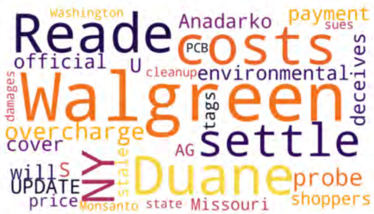
33		2012, 2014, 2016	CHK, DUK, EQT, SRE, TSO	Case 33: Environmental violation
34		2012, 2015	CVX, GM	Case 34: Environmental lawsuit and vehicle industry
35		2012, 2015, 2016	BBL, F, VALE.P	Case 35: Environmental incident / Brazil mine disaster and updates

36		2011, 2012	BP, COP, CVX, HES, VLO, XOM	Case 36: Refinery glitches and maintenance
37		2011, 2012, 2013, 2015, 2016	NVO, TM, TSLA	Case 37: Project competition and challenges / *
38		2012, 2016	DOW, JPM	Case 38: Environmental regulation

39		2012, 2013, 2014	DUK, FE, LMT, STO, THG	Case 39: Environmental regulation
40		2015	XOM	Case 40: Environmental regulation and policy / in New Jersey / Exxon
41		2012, 2013	BP	Case 41: Project related to environment / Drill and exploration

42		2012, 2013, 2014, 2015, 2016	BLK, C, GS, HPQ, IBM, KITE, USB, WFC	Case 42: Trading and asset activities
43		-	-	Case 43: NA
44		-	-	Case 44: NA

45		2012, 2013, 2014	DUK, ENB, SU, TRP	Case 45: Environmental concerns / pollution / oil sands
46		2012, 2013, 2015, 2016	AMZN, IBM, MET, MHG, NGG, SBUX, TM, UN, WBA, WMT	Case 46: Environmental strategy initiation
47		2012, 2014	COP, GM, MON, PKX	Case 47: Approval and support

48		2011, 2012, 2013, 2014, 2016	AERI, BA, BCS, CBS, CSCO, EBAY, GS, HON, ICE, JPM, KO, MCD, NDAQ, NOC, SHLD, TEF, TOT, TSN, WMT	Case 48: Financing / Debt, sales, interests
49		2015, 2016	BRK.A, GM, TM	Case 49: Environmental scandal and updates / VW case
50		2014, 2015, 2016	AEUA, MON, WBA	Case 50: Investigation and punishment

51 

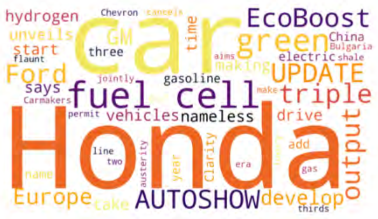
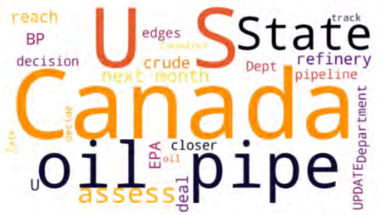
Case 51: NA

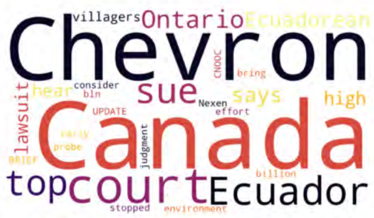
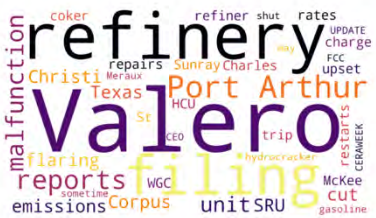
52 

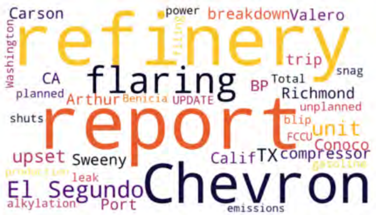
Case 52: NA

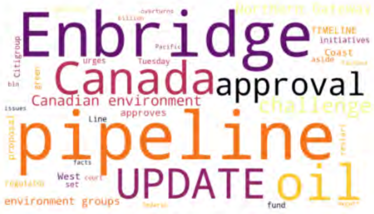
53 

2011, 2012 BP, COP, CVX, TSO, XOM Case 53: Refinery glitches and maintenance

54		2011, 2012, 2013, 2016	CVX, F, GM, HMC	Case 54: Environment, vehicle, cost and technology
55		2011, 2012	BP, ENB, TRP	Case 55: Deal and assessment on environmental projects
56		2011, 2012, 2013, 2014, 2015, 2016	AMZN, BAK, CVX, OIBR.C, PBR, SNE	Case 57: Events in Brazil market

57		2016, 2017	FDX, WBA	Case 57: events related Walgreens
58		2012, 2014, 2015	CEO, CVX	Case 58: Environmental lawsuits related to Chevron / in Canada
59		2011, 2012, 2014	VLO	Case 59: Valero refinery's glitches, reporting, and updates

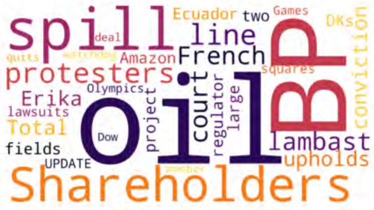
60				Case 60; NA
61		2011, 2012	BP, COP, CVX, TOT, TSO, VLO	Case 61: Carson refinery’s glitches, reporting and updates
62		2013, 2014, 2015, 2016	DB, KMI, MRK	Case 62: NA/reexamination

63		2012, 2013, 2014, 2015, 2016	C, ENB	Case 63: Environmental projects initialization and challenges
64		2011, 2012, 2013, 2014, 2015, 2016	TRP	Case 64: Events related to the Keystone pipeline
65		2013, 2015, 2016	AMOV, BBL, F, GG, KO, SAN, WBA	Case 65: Events in Mexico

66		2012, 2015, 2016, 2017	AMZN, BA, GS, IIJI, MT, TOT, TSLA	Case 66: Environmental summit and policies
67		2011, 2012, 2013, 2014, 2016	AMOV, AMZN, BA, BP, CEO, DB, FDX, GM, KKR, MB, MRK, NMR, TGT, TMUSP	Case 67: "Green light" and approval
68		2011, 2012, 2014, 2015, 2016	BA, BBL, GEB, HMC, MDLZ, NGG, RYAAY	Case 68: Environmental regulation and planning

69		2011, 2015, 2016	APPL, AIG, CVX, KO, XOM	Case 69: Environmental governance
70		2013, 2014, 2015	CVX	Case 70: CHEVRON’s Ecuador dispute and updates
71		2011, 2012, 2014, 2015, 2016	AMZN, BA, BCS, BLK, BP, CAT, CHK, CSIQ, CVX, DB, ENB, GEB, GTN, HLF, KO, NYT, SBUX, STT, TI, TM	Case 71: Sustainability investment-related events

72



2012, 2014

AMZN, BP, DOW, TOT

Case 72: Controversial projects and responsibilities related to the environment

73

Case 73: NA

74

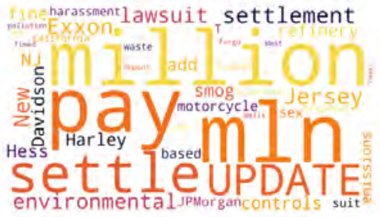
Case 74: Capital and market activities *

<table>
<tr><td>75</td><td>
</td><td>2011, 2012, 2013, 2015</td><td>DO, DOW, MON</td><td>Case 75; Monsanto’s activities and updates</td></tr>
<tr><td>76</td><td>
</td><td>2011, 2012, 2013, 2014, 2015, 2016</td><td>HSBC, KO, NVO, SNY, T, TI</td><td>Case 76: Deal and approval for companies’ activities</td></tr>
<tr><td>77</td><td>
</td><td>-</td><td>-</td><td>Case 77: NA</td></tr>
</table>

78		2011, 2015, 2016		Case 78: Activities related to plants
79		2013, 2016	CAT, HOG	Case 79: Environmental violation and investigation by federal prosecutors
80		2012, 2014, 2015, 2016	BBL, RIO, VALE.P	Case 80: Events related to Iron supply

81		2012, 2013, 2014, 2016	AAL, JBLU, RYAAY	Case 81: Activities related to airlines
82		2011, 2013, 2014, 2015, 2016	AAPL, AMZN, BP, CX, KO, SLB, SRE, TRP	Case 82: Carbon emissions
83		2013, 2014, 2016, 2017	CVX, GEB, JPM, KMI	Case 83: Expansion project affects the environment

84		2011, 2013, 2014, 2015, 2016, 2017	C, CYH, KMI, KO, KSS, LMT, NFLX, TOT, VIP	Case 84: Falling expectation
85		2011, 2014, 2015	BA, BBL, LPL	Case 85: Sustainability Concern / *
86		2011, 2014, 2016	CMI, DOW, NAV, XOM	Case 86: Emission

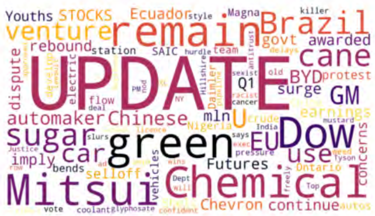
87		2012, 2014, 2015, 2016	DD, HES, HOG, JPM, T, WFC, XOM	Case 87: Environmental fine and settlement
88		2014, 2015, 2016	AMZN, MS, TI, UN	Case 88: Green trade and deal / NA
89		2012, 2013, 2016	AMZN, APO, BX, KKR, LMT, RYAAY, UN	Case 59: Unexpected earnings / loss

<table>
<tr><td>90</td><td>
</td><td>2012, 2013, 2015</td><td>AMZN, CVX</td><td>Case 90: Sustainability judgment and oil company</td></tr>
<tr><td>91</td><td>
</td><td>2011, 2012, 2014, 2015, 2016</td><td>BA, CVX, F, HPQ, JNS, MON, UAL, XOM</td><td>Case 91: Environmental regulation / carbon / European</td></tr>
<tr><td>92</td><td>
</td><td>2011, 2012, 2014, 2015, 2016</td><td>APPL, AMZN, EBAY, GEB, GOOG, PCG, STO, TOT</td><td>Case 92: Green energy</td></tr>
</table>

93		2012, 2013, 2014, 2016, 2017	BW, FB, F, HMC, TSLA	Case 93: Environmental trading and M&A
94		2011. 2014. 2015. 2016	DB GS NAV NKE	Case 94: NA
95		2011 2012 2014 2015 2016	DB RYAAY RYAAY TMUSP	Case 95: Carbon trading

96		2012 2013 2014 2015 2016	AEB AET AGU BLK DAL E MCD PEP TOT VLO	Case 96: Changes of governance and leadership
97		2014 2015 2016 2017	APA BAC CVS HAL MON NRG PBR	Case 97: A mix of events relating to the oil industry
98		2011 2012 2014 2015	BBL BP COP CVX E TOT XOM	Case 98: Gas M&A and permit

99		2012 2013 2014 2015 2016	BP BUD DB GSK NVO SAN SAP SNE TM	Case 99: NA
100		2011 2012 2013 2014 2015 2016	AAPL AEUA BLDP CEO COP F MCD NKE PTR SNP	Case 100: Environmental Investigation and Checks
101		2011 2012 2014 2015 2016	AMZN BBL CVX GS OIBR.C PBR VALE.P	Case 101: Brazil Environmental Events

102		2011 2012 2013 2014 2015 2016	FCAU F TM	Case 102: Toyota Environmental events
103		2011 2014 2015 2016	BRK.A CVX DIS DOW E F GM HON MON TRP TSN WPPGY	Case 103: NA
104		2012 2013 2016	AMZN PSX PSX TSO XOM	Case 105: Oil projects

105		2014 2016	BP GILD GIS	Case 105: NA
106		2012 2013 2015	DIS SBUX TSO	Case 106: NA
107		2012 2013 2014 2016	BRK.A F GM PTR TM TSLA	Case 107: Vehicle industry and program

108		2015	TRP	Case 108: Keystone carbon footprint
109		2013 2016	MA SIRI	Case 109: Supreme court lawsuits and company control
110		2011 2013 2015	TRP	Case 110: Events related to Keystone

111		2017	TM	Case 111: Volkswagen’s settlement
112		2011 2013 2014 2016	BBL DD DIS ERIC GM NAV TSLA	Case 112: NA
113		2012 2014	CVX XOM	Case 113: Activities related to environmental incidents

114		2012 2015 2016	AAPL LMT NOC UPS VALE.P	Case 115: Injunction and lawsuits
115		2011 2012 2014 2015	AAPL CVX DB DOW EC KMI PEP TOT	Case 115: NA
116		2011 2012 2014 2015 2016	AA AAPL BA BP MPC NFLX POT WLL	Case 116: Environmental agreement

117		2011 2012 2013 2014	BP TOT VLO	Case 117: Events related to refinery-filing
118		2015 2016	BUD FCAU F GS	Case 118: European vehicle industry and market
119		2011 2012 2014	GEB HSBC RYAAY TEF	Case 119: NA

120		2012, 2013, 2014, 2015, 2016	BABA BLK DOW HSBC LFL LYG NBHC OIBR.C RIO TI	Case 120: Government approval

6.5. Appendix V: Event Study Results of Each Event Cluster

Event study results of cluster 1

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.002	0.002	0.011	0.625	0.738
1	5	-0.002	0.001	0.008	1.000	0.690
2	5	-0.002	0.001	0.009	1.000	0.634
3	5	-0.005	-0.002	0.008	0.313	0.234
4	5	-0.007	-0.007	0.007	0.125	0.094
5	5	-0.011	-0.015	0.009	0.125	0.050†
(0,1)	5	0.000	-0.001	0.005	1.000	0.936
(0,5)	5	-0.009	-0.009	0.014	0.313	0.198
(0,10)	5	-0.012	-0.016	0.011	0.125	0.067†

Event study results of cluster 2

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.014	-0.026	0.046	0.625	0.526
1	5	-0.041	-0.064	0.070	0.313	0.266
2	5	-0.039	-0.053	0.067	0.313	0.267
3	5	-0.037	-0.048	0.069	0.313	0.295
4	5	-0.024	-0.008	0.065	0.313	0.457
5	5	-0.013	0.010	0.070	0.813	0.709
(0,1)	5	-0.026	-0.033	0.027	0.125	0.093
(0,5)	5	0.002	0.008	0.046	1.000	0.932†
(0,10)	5	0.002	0.010	0.039	0.813	0.894

Event study results of cluster 3

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	14	0.001	-0.002	0.030	0.952	0.884
1	14	0.004	0.005	0.031	0.626	0.672
2	14	0.004	-0.001	0.030	0.715	0.628
3	14	0.006	0.006	0.034	0.463	0.491
4	14	0.004	0.007	0.035	0.670	0.666
5	14	0.008	0.006	0.026	0.268	0.254
(0,1)	14	0.002	0.002	0.010	0.326	0.388
(0,5)	14	0.007	0.006	0.015	0.153	0.100
(0,10)	14	0.001	0.000	0.022	1.000	0.921

Event study results of cluster 4

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	-0.012	-0.011	0.033	0.266	0.250
1	12	-0.012	-0.010	0.034	0.339	0.254
2	12	-0.007	-0.009	0.033	0.519	0.493
3	12	-0.008	0.003	0.034	0.622	0.422
4	12	-0.007	0.002	0.034	0.733	0.490
5	12	-0.003	0.003	0.032	0.910	0.753
(0,1)	12	0.000	0.003	0.015	0.970	0.972
(0,5)	12	0.009	0.010	0.018	0.092†	0.130
(0,10)	12	0.002	0.010	0.020	0.622	0.754

Event study results of cluster 5

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.01	-0.01	0.01	0.13	0.11
1	9	-0.01	-0.01	0.02	0.25	0.29
`2	9	-0.01	-0.01	0.02	0.16	0.34
3	9	-0.01	-0.01	0.02	0.16	0.20
4	9	-0.01	-0.01	0.02	0.10	0.11
5	9	-0.02	-0.02	0.02	0.07†	0.06†
(0,1)	9	0.00	0.00	0.01	0.65	0.77
(0,5)	9	-0.01	-0.01	0.01	0.10	0.06†
(0,10)	9	0.00	0.00	0.01	0.13	0.65

Event study results of cluster 6

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	16	0.084	0.004	0.391	0.900	0.407
1	16	0.070	-0.001	0.357	0.706	0.443
2	16	0.074	0.004	0.373	0.821	0.437
3	16	0.056	0.000	0.307	0.782	0.479
4	16	0.073	0.002	0.340	0.900	0.402
5	16	0.075	0.006	0.326	0.669	0.373
(0,1)	16	-0.013	-0.003	0.037	0.144	0.169
(0,5)	16	-0.009	0.002	0.074	0.744	0.644
(0,10)	16	0.010	0.003	0.070	0.404	0.581

Event study results of cluster 7

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	11	0.001	-0.003	0.028	0.831	0.923
1	11	0.005	0.002	0.032	0.831	0.649
2	11	0.002	-0.003	0.029	0.898	0.807
3	11	0.005	-0.006	0.034	0.966	0.619
4	11	0.005	0.002	0.029	1.000	0.591
5	11	0.004	0.002	0.032	0.898	0.693
(0,1)	11	0.004	0.002	0.009	0.240	0.204
(0,5)	11	0.003	0.007	0.012	0.413	0.417
(0,10)	11	0.002	0.004	0.026	0.700	0.805

Event study results of cluster 8

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	0.008	0.015	0.037	0.461	0.536
1	8	0.005	0.009	0.035	0.547	0.695
2	8	0.009	0.011	0.039	0.547	0.547
3	8	0.009	0.014	0.041	0.547	0.568
4	8	0.009	0.013	0.040	0.547	0.556
5	8	0.007	0.012	0.038	0.641	0.615
(0,1)	8	-0.003	-0.003	0.005	0.109	0.114
(0,5)	8	-0.001	0.001	0.013	0.844	0.758
(0,10)	8	0.002	-0.001	0.012	0.844	0.624

Event study results of cluster 9

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.007	-0.009	0.010	0.250	0.279
1	4	-0.010	-0.014	0.015	0.250	0.267
2	4	-0.011	-0.016	0.019	0.375	0.332
3	4	-0.012	-0.019	0.021	0.375	0.323
4	4	-0.012	-0.021	0.027	0.375	0.444
5	4	-0.013	-0.021	0.027	0.625	0.389
(0,1)	4	-0.003	-0.005	0.005	0.250	0.244
(0,5)	4	-0.007	-0.008	0.019	0.625	0.537
(0,10)	4	-0.016	-0.017	0.016	0.250	0.132

Event study results of cluster 10

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.002	0.025	0.042	1.000	0.955
1	3	0.001	0.024	0.047	1.000	0.975
2	3	0.004	0.031	0.051	1.000	0.901
3	3	0.007	0.026	0.042	1.000	0.796
4	3	0.007	0.028	0.044	1.000	0.810
5	3	0.009	0.035	0.049	1.000	0.770
(0,1)	3	-0.001	-0.002	0.006	1.000	0.892
(0,5)	3	0.008	0.010	0.007	0.250	0.191
(0,10)	3	0.002	0.004	0.004	0.500	0.427

Event study results of cluster 11

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	-0.021	0.047	0.197	1.000	0.871
1	3	0.022	0.050	0.194	0.750	0.863
2	3	0.045	0.036	0.169	0.750	0.692
3	3	0.041	0.030	0.168	0.750	0.715
4	3	0.051	0.034	0.130	0.750	0.565
5	3	0.079	0.042	0.076	0.250	0.212
(0,1)	3	0.043	0.058	0.034	0.250	0.163
(0,5)	3	0.100	0.033	0.162	0.500	0.397
(0,10)	3	0.101	0.006	0.200	0.750	0.474

Event study results of cluster 12

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	27	0.002	-0.002	0.059	0.866	0.858
1	27	0.001	-0.001	0.052	0.923	0.935
2	27	0.002	0.000	0.048	0.848	0.788
3	27	-0.001	-0.001	0.055	0.885	0.939
4	27	0.001	0.003	0.052	0.904	0.918
5	27	0.001	0.002	0.057	0.923	0.959
(0,1)	27	-0.001	0.000	0.010	0.614	0.511
(0,5)	27	-0.001	-0.001	0.013	0.810	0.569
(0,10)	27	0.000	0.000	0.019	0.904	0.997

Event study results of cluster 13

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.046	0.007	0.132	0.432	0.303
1	10	0.074	0.008	0.226	0.492	0.328
2	10	0.087	0.008	0.226	0.375	0.253
3	10	0.097	0.009	0.248	0.193	0.250
4	10	0.094	0.005	0.234	0.322	0.237
5	10	0.097	0.007	0.246	0.160	0.244
(0,1)	10	0.028	-0.003	0.097	0.846	0.381
(0,5)	10	0.051	0.004	0.117	0.131	0.198
(0,10)	10	0.076	0.023	0.161	0.084	0.171

Event study results of cluster 14

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.001	-0.009	0.047	1.000	0.966
1	5	0.002	0.005	0.049	1.000	0.916
2	5	0.000	0.003	0.059	1.000	0.994
3	5	0.002	0.007	0.057	1.000	0.950
4	5	0.008	0.020	0.055	0.813	0.766
5	5	0.006	0.021	0.060	0.813	0.841
(0,1)	5	0.003	0.004	0.019	0.813	0.707
(0,5)	5	0.007	0.012	0.026	0.625	0.588
(0,10)	5	0.015	0.009	0.064	0.625	0.625

Event study results of cluster 15

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	0.038	0.055	0.062	0.313	0.248
1	5	0.045	0.066	0.056	0.188	0.148
2	5	0.040	0.060	0.064	0.313	0.229
3	5	0.045	0.060	0.058	0.188	0.155
4	5	0.049	0.061	0.051	0.188	0.098
5	5	0.044	0.053	0.037	0.063	0.056
(0,1)	5	0.007	0.007	0.011	0.313	0.196
(0,5)	5	0.006	0.003	0.026	0.625	0.626
(0,10)	5	0.001	-0.003	0.033	0.813	0.932

Event study results of cluster 16

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.016	-0.025	0.070	0.426	0.504
1	9	-0.014	-0.021	0.065	0.426	0.529
2	9	-0.021	-0.018	0.065	0.301	0.368
3	9	-0.009	-0.021	0.056	0.570	0.650
4	9	-0.011	-0.026	0.058	0.426	0.578
5	9	-0.004	-0.012	0.060	0.734	0.845
(0,1)	9	0.002	-0.001	0.017	1.000	0.733
(0,5)	9	0.012	0.002	0.026	0.203	0.205
(0,10)	9	0.005	0.000	0.037	0.570	0.715

Event study results of cluster 17

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	20	-0.019	-0.019	0.034	0.017*	0.024*
1	20	-0.021	-0.018	0.038	0.007*	0.020*
2	20	-0.016	-0.014	0.048	0.021*	0.160
3	20	-0.016	-0.018	0.047	0.033*	0.138
4	20	-0.014	-0.018	0.058	0.033*	0.289
5	20	-0.016	-0.016	0.050	0.036*	0.162
(0,1)	20	-0.002	-0.001	0.008	0.261	0.197
(0,5)	20	0.003	-0.001	0.021	0.985	0.557
(0,10)	20	0.009	-0.003	0.071	0.430	0.566

Event study results of cluster 18

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	-0.687	-0.002	1.679	0.547	0.285
1	8	-0.700	-0.009	1.681	0.547	0.277
2	8	-0.683	-0.013	1.674	0.461	0.286
3	8	-0.694	-0.010	1.680	0.547	0.281
4	8	-0.637	0.000	1.685	0.641	0.321
5	8	-0.654	0.004	1.667	0.844	0.304
(0,1)	8	-0.013	-0.020	0.055	0.250	0.516
(0,5)	8	0.033	-0.017	0.137	0.945	0.517
(0,10)	8	0.025	-0.032	0.251	0.945	0.783

Event study results of cluster 19

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	-0.065	-0.047	0.089	0.016*	0.028*
1	12	-0.065	-0.039	0.088	0.012*	0.027*
2	12	-0.066	-0.045	0.092	0.016*	0.029*
3	12	-0.072	-0.045	0.100	0.009**	0.031*
4	12	-0.065	-0.043	0.094	0.016*	0.035*
5	12	-0.074	-0.052	0.104	0.009**	0.031*
(0,1)	12	0.000	0.001	0.019	0.569	0.941
(0,5)	12	-0.009	-0.005	0.023	0.266	0.205
(0,10)	12	-0.003	-0.004	0.022	0.301	0.645

Event study results of cluster 20

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	19	0.003	0.007	0.039	0.418	0.771
1	19	0.004	0.008	0.037	0.395	0.670
2	19	0.004	0.010	0.039	0.312	0.654
3	19	0.009	0.012	0.035	0.123	0.281
4	19	0.008	0.007	0.039	0.275	0.385
5	19	0.008	0.008	0.042	0.196	0.395
(0,1)	19	0.001	0.001	0.003	0.196	0.189
(0,5)	19	0.006	0.004	0.013	0.134	0.064
(0,10)	19	0.006	0.004	0.017	0.210	0.179

Event study results of cluster 21

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	16	-0.007	0.005	0.050	0.860	0.606
1	16	-0.006	0.005	0.044	0.706	0.616
2	16	-0.007	0.003	0.048	0.782	0.585
3	16	-0.008	0.003	0.052	0.860	0.554
4	16	-0.004	0.004	0.044	0.821	0.741
5	16	-0.004	-0.001	0.038	0.669	0.711
(0,1)	16	0.001	0.000	0.014	0.597	0.783
(0,5)	16	0.003	-0.002	0.024	1.000	0.631
(0,10)	16	-0.012	-0.008	0.020	0.034*	0.032*

Event study results of cluster 22

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	18	0.001	0.010	0.045	0.899	0.892
1	18	0.004	0.010	0.041	0.734	0.704
2	18	0.002	0.006	0.044	0.702	0.860
3	18	0.000	-0.002	0.042	1.000	0.997
4	18	0.001	0.007	0.042	0.799	0.937
5	18	0.001	-0.001	0.043	0.966	0.890
(0,1)	18	0.002	0.000	0.015	1.000	0.515
(0,5)	18	0.000	-0.003	0.021	0.734	0.991
(0,10)	18	0.007	0.012	0.023	0.265	0.215

Event study results of cluster 23

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.012	0.003	0.049	0.432	0.453
1	10	0.010	0.004	0.049	0.432	0.551
2	10	0.013	0.003	0.038	0.492	0.301
3	10	0.013	0.004	0.038	0.375	0.306
4	10	0.015	0.006	0.045	0.375	0.310
5	10	0.020	0.006	0.050	0.375	0.239
(0,1)	10	-0.002	0.000	0.007	0.557	0.300
(0,5)	10	0.008	0.005	0.008	0.004**	0.011*
(0,10)	10	0.012	0.009	0.012	0.010	0.014

Event study results of cluster 24

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	11	-0.003	-0.016	0.045	0.365	0.841
1	11	-0.006	-0.005	0.042	0.365	0.625
2	11	-0.003	-0.005	0.042	0.320	0.807
3	11	-0.006	-0.007	0.042	0.240	0.656
4	11	-0.001	-0.008	0.035	0.320	0.925
5	11	-0.009	-0.009	0.043	0.278	0.492
(0,1)	11	-0.004	-0.002	0.015	0.206	0.438
(0,5)	11	-0.006	0.000	0.027	0.520	0.458
(0,10)	11	-0.019	-0.021	0.018	0.014*	0.006**

Event study results of cluster 25

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	-0.033	-0.036	0.049	0.033	0.032*
1	13	-0.033	-0.042	0.048	0.033*	0.029*
2	13	-0.040	-0.046	0.046	0.008**	0.008**
3	13	-0.049	-0.046	0.047	0.005**	0.003**
4	13	-0.046	-0.046	0.049	0.010*	0.005**
5	13	-0.043	-0.044	0.052	0.017*	0.011*
(0,1)	13	0.000	-0.004	0.010	0.635	0.978
(0,5)	13	-0.010	-0.008	0.031	0.340	0.245
(0,10)	13	-0.002	0.000	0.040	1.000	0.879

Event study results of cluster 26

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	-0.005	-0.004	0.060	0.677	0.763
1	12	-0.004	-0.012	0.062	0.970	0.820
2	12	-0.002	-0.011	0.072	0.910	0.919
3	12	-0.003	-0.007	0.066	0.910	0.866
4	12	0.000	0.002	0.064	0.850	0.999
5	12	0.001	0.005	0.064	0.910	0.975
(0,1)	12	0.001	0.003	0.011	0.677	0.703
(0,5)	12	0.006	0.003	0.024	0.424	0.408
(0,10)	12	-0.004	0.011	0.043	0.850	0.749

Event study results of cluster 27

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	0.026	0.018	0.024	0.063†	0.072†
1	5	0.027	0.034	0.015	0.063†	0.017*
2	5	0.032	0.034	0.010	0.063†	0.002**
3	5	0.034	0.032	0.016	0.063†	0.009**
4	5	0.037	0.031	0.020	0.063†	0.015*
5	5	0.030	0.028	0.033	0.125	0.116
(0,1)	5	0.001	0.003	0.017	0.625	0.935
(0,5)	5	0.004	0.015	0.025	0.813	0.750
(0,10)	5	0.032	0.032	0.071	0.625	0.370

Event study results of cluster 28

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.003	0.002	0.054	0.910	0.827
1	12	-0.001	-0.001	0.051	0.850	0.921
2	12	-0.005	0.002	0.076	0.910	0.818
3	12	-0.003	0.001	0.068	0.970	0.876
4	12	-0.002	0.000	0.075	0.970	0.913
5	12	-0.004	0.001	0.071	0.970	0.846
(0,1)	12	-0.005	-0.002	0.015	0.424	0.279
(0,5)	12	-0.008	0.001	0.026	0.733	0.341
(0,10)	12	-0.005	0.009	0.055	0.677	0.752

Event study results of cluster 29

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	-0.073	-0.073	0.100	0.500	0.488
1	2	-0.077	-0.077	0.102	0.500	0.479
2	2	-0.070	-0.070	0.098	0.500	0.495
3	2	-0.066	-0.066	0.091	0.500	0.490
4	2	-0.079	-0.079	0.105	0.500	0.481
5	2	-0.059	-0.059	0.077	0.500	0.476
(0,1)	2	-0.004	-0.004	0.002	0.500	0.222
(0,5)	2	0.015	0.015	0.023	1.000	0.533
(0,10)	2	0.005	0.005	0.021	1.000	0.781

Event study results of cluster 30

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.012	-0.005	0.030	0.301	0.272
1	9	-0.013	-0.006	0.034	0.359	0.268
2	9	-0.016	-0.006	0.041	0.426	0.286
3	9	-0.010	-0.002	0.032	0.570	0.384
4	9	-0.018	0.000	0.046	0.570	0.275
5	9	-0.014	-0.009	0.034	0.359	0.252
(0,1)	9	-0.002	0.000	0.009	0.820	0.627
(0,5)	9	-0.002	0.000	0.011	0.652	0.566
(0,10)	9	-0.015	-0.016	0.025	0.129	0.109

Event study results of cluster 31

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	0.047	0.055	0.132	0.383	0.346
1	8	0.056	0.046	0.125	0.313	0.250

2	8	0.047	0.052	0.129	0.383	0.333
3	8	0.062	0.050	0.147	0.383	0.271
4	8	0.018	0.057	0.147	0.844	0.737
5	8	0.030	0.059	0.151	0.461	0.587
(0,1)	8	0.008	-0.003	0.035	0.945	0.529
(0,5)	8	-0.017	-0.004	0.070	0.742	0.517
(0,10)	8	-0.046	-0.018	0.072	0.195	0.113

Event study results of cluster 32

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.048	0.046	0.047	0.020*	0.016*
1	9	0.049	0.047	0.046	0.020*	0.012*
2	9	0.048	0.035	0.051	0.020*	0.024*
3	9	0.054	0.058	0.049	0.020*	0.011*
4	9	0.048	0.037	0.050	0.020*	0.022*
5	9	0.049	0.032	0.055	0.020*	0.028*
(0,1)	9	0.001	0.000	0.009	0.820	0.708
(0,5)	9	0.001	-0.006	0.017	1.000	0.891
(0,10)	9	0.011	0.014	0.021	0.203	0.158

Event study results of cluster 33

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.008	0.010	0.049	1.000	0.748
1	5	-0.019	0.004	0.072	1.000	0.576
2	5	-0.018	0.007	0.075	1.000	0.613
3	5	-0.027	0.007	0.095	1.000	0.561
4	5	-0.020	0.003	0.095	0.813	0.662
5	5	-0.008	0.008	0.087	0.625	0.844
(0,1)	5	-0.012	-0.004	0.026	0.438	0.359
(0,5)	5	-0.001	-0.001	0.046	1.000	0.978
(0,10)	5	0.005	0.004	0.052	0.813	0.826

Event study results of cluster 34

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.034	-0.045	0.062	0.375	0.347
1	4	-0.035	-0.057	0.047	0.250	0.239
2	4	-0.037	-0.047	0.058	0.375	0.291
3	4	-0.027	-0.044	0.054	0.375	0.387
4	4	-0.038	-0.055	0.059	0.250	0.288
5	4	-0.030	-0.051	0.051	0.250	0.327
(0,1)	4	0.000	0.000	0.030	1.000	0.977
(0,5)	4	0.005	0.011	0.036	0.875	0.811
(0,10)	4	0.001	0.019	0.066	0.875	0.968

Event study results of cluster 35

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.015	0.012	0.007	0.250	0.062
1	3	0.002	0.011	0.028	1.000	0.931
2	3	0.008	0.013	0.023	0.750	0.622
3	3	0.004	0.008	0.028	0.750	0.828
4	3	0.011	0.008	0.023	0.750	0.484
5	3	0.013	0.009	0.025	0.750	0.460
(0,1)	3	-0.014	0.000	0.024	0.750	0.424
(0,5)	3	-0.002	-0.002	0.019	0.750	0.854
(0,10)	3	0.006	-0.002	0.015	1.000	0.551

Event study results of cluster 36

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	11	-0.009	-0.009	0.066	1.000	0.647
1	11	-0.018	-0.024	0.077	0.831	0.462
2	11	-0.017	-0.026	0.075	0.831	0.454
3	11	-0.028	-0.024	0.077	0.413	0.257
4	11	-0.034	-0.025	0.084	0.465	0.214
5	11	-0.033	-0.012	0.089	0.465	0.241
(0,1)	11	-0.008	-0.002	0.018	0.278	0.156
(0,5)	11	-0.024	-0.012	0.058	0.278	0.197
(0,10)	11	-0.012	-0.011	0.063	0.765	0.528

Event study results of cluster 37

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	0.007	-0.012	0.080	0.945	0.809
1	8	0.000	-0.021	0.095	0.945	0.989
2	8	-0.003	-0.017	0.103	0.945	0.944
3	8	-0.012	-0.012	0.120	0.945	0.788
4	8	-0.015	-0.024	0.127	0.945	0.741
5	8	-0.017	-0.025	0.131	1.000	0.720
(0,1)	8	-0.008	-0.009	0.016	0.250	0.234
(0,5)	8	-0.024	-0.007	0.062	0.547	0.306
(0,10)	8	-0.030	-0.025	0.083	0.383	0.337

Event study results of cluster 38

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.006	0.006	0.023	0.750	0.685
1	3	0.000	-0.001	0.019	0.750	0.971
2	3	0.000	0.001	0.027	0.750	0.980
3	3	0.007	0.009	0.013	0.500	0.468
4	3	0.016	0.007	0.032	0.750	0.465
5	3	0.011	0.006	0.027	0.750	0.542
(0,1)	3	-0.007	-0.007	0.003	0.250	0.081
(0,5)	3	0.005	0.012	0.022	0.750	0.716
(0,10)	3	0.012	0.025	0.032	0.500	0.574

Event study results of cluster 39

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.015	0.010	0.017	0.014*	0.019*
1	10	0.016	0.007	0.020	0.020*	0.034*
2	10	0.014	0.006	0.023	0.037*	0.095†
3	10	0.017	0.010	0.023	0.037*	0.046*
4	10	0.019	0.012	0.027	0.037*	0.054†
5	10	0.019	0.015	0.029	0.037*	0.062*
(0,1)	10	0.001	0.000	0.005	0.846	0.508
(0,5)	10	0.004	0.000	0.016	0.625	0.384
(0,10)	10	0.008	-0.003	0.023	1.000	0.276

Event study results of cluster 40

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	-0.042	-0.057	0.044	0.156	0.068†
1	6	-0.040	-0.048	0.042	0.094†	0.065†
2	6	-0.042	-0.060	0.049	0.094†	0.089†
3	6	-0.032	-0.049	0.046	0.156	0.144
4	6	-0.041	-0.051	0.050	0.094†	0.105
5	6	-0.044	-0.060	0.048	0.094†	0.077†
(0,1)	6	0.002	-0.001	0.009	1.000	0.558
(0,5)	6	-0.001	0.002	0.017	1.000	0.848
(0,10)	6	0.000	0.000	0.009	1.000	0.900

Event study results of cluster 41

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	0.033	0.033	0.037	0.500	0.426
1	2	0.042	0.042	0.041	0.500	0.387
2	2	0.026	0.026	0.040	1.000	0.517
3	2	0.034	0.034	0.051	1.000	0.521
4	2	0.035	0.035	0.057	1.000	0.548
5	2	0.020	0.020	0.027	0.500	0.490
(0,1)	2	0.008	0.008	0.004	0.500	0.197
(0,5)	2	-0.013	-0.013	0.010	0.500	0.311
(0,10)	2	0.000	0.000	0.034	1.000	0.997

Event study results of cluster 42

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.055	0.007	0.225	0.625	0.458
1	10	0.046	-0.001	0.218	0.770	0.518
2	10	0.045	-0.005	0.246	0.846	0.574
3	10	0.037	-0.006	0.226	0.846	0.615
4	10	0.037	-0.005	0.240	0.846	0.639
5	10	0.023	-0.004	0.257	0.922	0.784
(0,1)	10	-0.009	-0.008	0.013	0.049	0.058
(0,5)	10	-0.032	-0.009	0.066	0.322	0.156
(0,10)	10	-0.023	-0.009	0.042	0.232	0.114

Event study results of cluster 43

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	29	0.012	-0.002	0.095	0.974	0.491
1	29	0.010	0.005	0.089	0.905	0.565
2	29	0.010	0.001	0.090	0.804	0.542
3	29	0.014	0.001	0.103	0.922	0.462
4	29	0.014	0.000	0.102	0.940	0.479
5	29	0.013	0.001	0.099	0.854	0.487
(0,1)	29	-0.003	0.000	0.016	0.524	0.384
(0,5)	29	0.001	0.005	0.020	0.524	0.850
(0,10)	29	0.007	0.001	0.054	0.974	0.509

Event study results of cluster 44

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.005	-0.015	0.130	0.734	0.908
1	9	-0.013	-0.028	0.134	0.652	0.784
2	9	-0.028	-0.012	0.146	0.652	0.576
3	9	-0.025	-0.020	0.160	0.570	0.654
4	9	-0.037	-0.017	0.186	0.496	0.568
5	9	-0.026	-0.020	0.176	0.734	0.673
(0,1)	9	-0.008	-0.004	0.017	0.203	0.211
(0,5)	9	-0.021	-0.005	0.064	0.301	0.362
(0,10)	9	-0.003	-0.023	0.073	0.301	0.920

Event study results of cluster 45

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	-0.007	-0.011	0.020	0.375	0.386
1	7	-0.006	-0.014	0.019	0.469	0.430
2	7	-0.007	-0.018	0.020	0.297	0.394
3	7	-0.009	-0.018	0.023	0.297	0.316
4	7	-0.009	-0.011	0.026	0.375	0.388
5	7	-0.013	-0.019	0.027	0.219	0.235
(0,1)	7	0.001	0.002	0.003	0.375	0.358
(0,5)	7	-0.006	-0.008	0.008	0.078	0.075
(0,10)	7	-0.008	-0.006	0.014	0.156	0.161

Event study results of cluster 46

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	0.013	0.014	0.077	0.588	0.548
1	13	0.005	0.015	0.060	0.685	0.769
2	13	0.003	0.014	0.062	0.787	0.861
3	13	-0.001	0.013	0.058	0.839	0.964
4	13	0.007	0.013	0.067	0.635	0.710
5	13	0.006	0.016	0.060	0.588	0.728
(0,1)	13	-0.008	0.000	0.038	1.000	0.449
(0,5)	13	-0.007	0.002	0.039	0.635	0.511
(0,10)	13	0.004	0.007	0.025	0.376	0.616

Event study results of cluster 47

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	18	0.031	0.024	0.046	0.007*	0.011*
1	18	0.035	0.021	0.052	0.002*	0.011*
2	18	0.036	0.024	0.053	0.004*	0.010*
3	18	0.037	0.030	0.051	0.001*	0.008*
4	18	0.034	0.020	0.054	0.003*	0.015*
5	18	0.031	0.017	0.057	0.016*	0.031*
(0,1)	18	0.004	0.002	0.017	0.325	0.345
(0,5)	18	0.000	0.012	0.036	0.580	0.964
(0,10)	18	-0.006	0.016	0.061	0.702	0.659

Event study results of cluster 48

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	0.013	0.014	0.077	0.588	0.548
1	13	0.005	0.015	0.060	0.685	0.769
2	13	0.003	0.014	0.062	0.787	0.861
3	13	-0.001	0.013	0.058	0.839	0.964
4	13	0.007	0.013	0.067	0.635	0.710
5	13	0.006	0.016	0.060	0.588	0.728
(0,1)	13	-0.008	0.000	0.038	1.000	0.449
(0,5)	13	-0.007	0.002	0.039	0.635	0.511
(0,10)	13	0.004	0.007	0.025	0.376	0.616

Event study results of cluster 49

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	0.034	0.030	0.032	0.063†	0.049*
1	6	0.036	0.040	0.033	0.094†	0.046*
2	6	0.027	0.025	0.031	0.156	0.085†
3	6	0.025	0.020	0.036	0.438	0.149
4	6	0.034	0.025	0.040	0.156	0.088†
5	6	0.026	0.023	0.058	0.438	0.315
(0,1)	6	0.002	0.001	0.016	0.844	0.771
(0,5)	6	-0.007	-0.012	0.040	0.844	0.675
(0,10)	6	-0.009	-0.001	0.053	0.438	0.710

Event study results of cluster 50

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.002	0.001	0.022	0.750	0.866
1	3	-0.007	0.003	0.034	1.000	0.747
2	3	-0.005	0.012	0.038	1.000	0.857
3	3	-0.013	0.014	0.057	1.000	0.736
4	3	-0.009	0.002	0.048	1.000	0.785
5	3	-0.017	-0.007	0.054	0.750	0.641
(0,1)	3	-0.010	-0.004	0.015	0.500	0.373
(0,5)	3	-0.019	-0.008	0.032	0.500	0.412
(0,10)	3	-0.012	-0.008	0.024	0.750	0.458

Event study results of cluster 51

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.001	0.006	0.050	0.938	0.954
1	7	0.004	0.010	0.049	0.938	0.838
2	7	0.006	0.013	0.054	0.938	0.775
3	7	0.006	0.013	0.050	0.938	0.766
4	7	0.005	0.011	0.047	0.938	0.766
5	7	0.010	0.009	0.044	0.813	0.572
(0,1)	7	0.003	0.003	0.005	0.297	0.163
(0,5)	7	0.009	0.008	0.019	0.297	0.275
(0,10)	7	0.003	0.004	0.012	0.578	0.563

Event study results of cluster 52

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	0.031	0.024	0.044	0.156	0.148
1	6	0.017	0.015	0.072	0.438	0.580
2	6	0.016	0.012	0.075	0.438	0.627
3	6	0.015	0.008	0.064	0.563	0.598
4	6	0.001	0.006	0.106	0.438	0.985
5	6	-0.002	0.010	0.103	0.563	0.966
(0,1)	6	-0.014	-0.005	0.034	0.563	0.376
(0,5)	6	-0.033	-0.006	0.070	0.438	0.306
(0,10)	6	-0.003	0.001	0.034	1.000	0.847

Event study results of cluster 53

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	19	0.021	0.026	0.024	0.002**	0.001**
1	19	0.019	0.028	0.027	0.008**	0.007**
2	19	0.020	0.022	0.027	0.002**	0.004**
3	19	0.017	0.022	0.030	0.020*	0.029*
4	19	0.020	0.028	0.032	0.032*	0.013*
5	19	0.019	0.033	0.038	0.029*	0.044*
(0,1)	19	-0.002	-0.002	0.009	0.490	0.371
(0,5)	19	-0.002	-0.001	0.026	0.984	0.736
(0,10)	19	0.001	0.000	0.026	0.768	0.891

Event study results of cluster 54

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	-0.003	0.000	0.039	0.945	0.821
1	8	-0.002	-0.001	0.039	0.844	0.887
2	8	-0.002	-0.001	0.038	0.844	0.880
3	8	-0.001	-0.003	0.037	0.945	0.962
4	8	-0.002	-0.009	0.037	0.945	0.874
5	8	0.000	-0.012	0.039	1.000	0.994
(0,1)	8	0.001	0.001	0.002	0.195	0.188
(0,5)	8	0.003	0.002	0.014	0.461	0.503
(0,10)	8	-0.003	-0.003	0.021	0.742	0.729

Event study results of cluster 55

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.028	-0.023	0.033	0.250	0.192
1	4	-0.030	-0.027	0.032	0.125	0.162
2	4	-0.025	-0.021	0.031	0.250	0.201
3	4	-0.030	-0.019	0.041	0.250	0.239
4	4	-0.025	-0.020	0.033	0.250	0.226
5	4	-0.025	-0.016	0.038	0.375	0.274
(0,1)	4	-0.002	-0.002	0.003	0.250	0.260
(0,5)	4	0.002	0.002	0.014	0.875	0.749
(0,10)	4	-0.016	-0.004	0.026	0.250	0.314

Event study results of cluster 56

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.200	0.072	0.440	0.105	0.185
1	10	0.190	0.067	0.385	0.105	0.152
2	10	0.163	0.071	0.440	0.160	0.271
3	10	0.158	0.054	0.432	0.160	0.276
4	10	0.157	0.058	0.424	0.160	0.272
5	10	0.144	0.067	0.414	0.084	0.299
(0,1)	10	-0.009	0.001	0.083	0.922	0.739
(0,5)	10	-0.055	-0.001	0.096	0.375	0.103
(0,10)	10	-0.044	0.006	0.183	0.770	0.466

Event study results of cluster 57

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.006	-0.006	0.023	0.496	0.468
1	9	0.001	0.006	0.031	0.910	0.942
2	9	0.000	0.007	0.024	1.000	0.992
3	9	-0.003	-0.005	0.030	0.820	0.780
4	9	-0.006	0.000	0.026	0.570	0.472
5	9	-0.004	-0.007	0.028	0.734	0.700
(0,1)	9	0.007	0.010	0.010	0.129	0.083
(0,5)	9	0.002	0.002	0.014	0.734	0.646
(0,10)	9	0.012	0.012	0.040	0.496	0.391

Event study results of cluster 58

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	-0.043	-0.020	0.075	0.500	0.427
1	3	-0.120	-0.107	0.128	0.500	0.245
2	3	-0.086	-0.122	0.080	0.500	0.205
3	3	-0.085	-0.084	0.107	0.500	0.305
4	3	-0.105	-0.123	0.097	0.250	0.201
5	3	-0.090	-0.111	0.077	0.250	0.182
(0,1)	3	-0.077	-0.087	0.055	0.250	0.138
(0,5)	3	-0.047	-0.027	0.038	0.250	0.170
(0,10)	3	0.050	0.055	0.096	0.500	0.467

Event study results of cluster 59

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	-0.004	-0.011	0.035	0.635	0.668
1	13	-0.009	-0.015	0.039	0.635	0.434
2	13	-0.003	-0.016	0.035	1.000	0.773
3	13	-0.005	-0.011	0.034	0.685	0.609
4	13	-0.002	-0.019	0.036	0.839	0.806
5	13	-0.004	-0.018	0.034	0.893	0.677
(0,1)	13	-0.005	-0.002	0.012	0.168	0.178
(0,5)	13	0.000	0.004	0.014	0.735	0.951
(0,10)	13	0.002	-0.001	0.027	0.946	0.788

Event study results of cluster 60

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	14	0.010	0.006	0.019	0.119	0.091†
1	14	0.021	0.016	0.019	0.001**	0.001**
2	14	0.017	0.011	0.018	0.004**	0.004**
3	14	0.019	0.012	0.023	0.007**	0.009**
4	14	0.019	0.012	0.020	0.001**	0.003**
5	14	0.021	0.020	0.019	0.001**	0.001**
(0,1)	14	0.011	0.005	0.018	0.030*	0.037*
(0,5)	14	0.012	0.009	0.016	0.020*	0.018*
(0,10)	14	0.010	0.005	0.025	0.194	0.146

Event study results of cluster 61

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	14	0.005	0.027	0.049	0.808	0.698
1	14	0.007	0.029	0.055	0.670	0.645
2	14	0.001	0.026	0.056	0.903	0.926
3	14	0.004	0.019	0.057	0.855	0.809
4	14	0.001	0.021	0.061	0.952	0.960
5	14	0.009	0.026	0.057	0.502	0.565
(0,1)	14	0.002	0.002	0.015	0.583	0.678
(0,5)	14	0.004	0.005	0.020	0.502	0.490
(0,10)	14	-0.001	-0.005	0.029	0.761	0.887

Event study results of cluster 62

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.019	-0.002	0.041	0.625	0.364
1	5	-0.019	-0.011	0.036	0.313	0.296
2	5	-0.019	-0.004	0.037	0.313	0.320
3	5	-0.017	-0.005	0.045	0.438	0.440
4	5	-0.020	-0.014	0.036	0.313	0.285
5	5	-0.018	-0.011	0.033	0.313	0.289
(0,1)	5	0.000	0.002	0.015	0.625	0.975
(0,5)	5	0.001	-0.003	0.019	1.000	0.926
(0,10)	5	0.003	0.006	0.017	0.625	0.689

Event study results of cluster 63

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.009	0.005	0.014	0.021*	0.044*
1	12	0.009	0.005	0.012	0.016*	0.029*
2	12	0.010	0.008	0.013	0.016*	0.019*
3	12	0.012	0.010	0.013	0.002*	0.011*
4	12	0.012	0.010	0.013	0.007*	0.010*
5	12	0.013	0.010	0.015	0.003*	0.012*
(0,1)	12	0.000	0.001	0.005	0.910	0.972
(0,5)	12	0.004	0.007	0.010	0.129	0.165
(0,10)	12	0.007	0.005	0.014	0.110	0.089

Event study results of cluster 64

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.000	0.000	0.014	0.910	0.990
1	12	-0.002	-0.004	0.017	0.424	0.687
2	12	0.001	-0.001	0.020	0.910	0.930
3	12	0.000	0.000	0.019	0.910	0.947
4	12	0.002	0.003	0.021	0.791	0.717
5	12	0.003	0.002	0.018	0.733	0.550
(0,1)	12	-0.002	-0.002	0.006	0.266	0.274
(0,5)	12	0.003	0.005	0.010	0.301	0.289
(0,10)	12	0.007	0.008	0.015	0.233	0.168

Event study results of cluster 65

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	-0.006	-0.012	0.022	0.469	0.467
1	7	-0.007	-0.006	0.024	0.813	0.440
2	7	-0.004	-0.001	0.021	0.813	0.631
3	7	-0.004	0.006	0.027	1.000	0.729
4	7	-0.001	0.008	0.026	1.000	0.935
5	7	0.001	0.005	0.029	0.813	0.899
(0,1)	7	-0.001	0.000	0.007	0.688	0.722
(0,5)	7	0.008	0.002	0.022	0.469	0.384
(0,10)	7	0.005	-0.001	0.014	0.938	0.383

Event study results of cluster 66

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.157	0.003	0.397	0.469	0.336
1	7	0.158	0.007	0.428	0.688	0.365
2	7	0.144	0.012	0.385	0.688	0.361
3	7	0.161	0.011	0.440	0.578	0.370
4	7	0.133	0.009	0.397	0.688	0.410
5	7	0.132	0.010	0.388	0.688	0.404
(0,1)	7	0.002	0.004	0.036	0.938	0.914
(0,5)	7	-0.025	-0.031	0.040	0.156	0.145
(0,10)	7	-0.019	-0.009	0.067	0.813	0.493

Event study results of cluster 67

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.000	-0.005	0.072	0.791	0.990
1	12	-0.003	-0.005	0.068	0.470	0.864
2	12	0.003	-0.002	0.067	0.791	0.878
3	12	0.003	-0.002	0.063	0.910	0.886
4	12	0.007	0.000	0.076	0.910	0.738
5	12	0.005	0.001	0.069	0.850	0.798
(0,1)	12	-0.003	0.000	0.018	0.677	0.560
(0,5)	12	0.005	0.000	0.023	0.677	0.432
(0,10)	12	0.006	0.003	0.020	0.380	0.351

Event study results of cluster 68

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.014	0.005	0.078	0.734	0.614
1	9	-0.016	0.008	0.093	0.496	0.615
2	9	-0.029	0.000	0.118	0.910	0.484
3	9	-0.027	0.000	0.112	1.000	0.487
4	9	-0.028	0.000	0.115	1.000	0.480
5	9	-0.019	0.001	0.102	0.570	0.584
(0,1)	9	-0.003	0.001	0.016	0.496	0.647
(0,5)	9	-0.006	0.002	0.027	1.000	0.545
(0,10)	9	-0.004	0.003	0.020	0.734	0.552

Event study results of cluster 69

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.004	0.001	0.045	0.469	0.803
1	7	0.002	-0.002	0.048	0.813	0.897
2	7	0.000	-0.002	0.046	1.000	0.983
3	7	-0.003	0.005	0.047	0.938	0.868
4	7	-0.008	0.010	0.057	0.813	0.721
5	7	-0.018	-0.025	0.066	0.688	0.493
(0,1)	7	-0.002	-0.001	0.006	0.219	0.404
(0,5)	7	-0.023	-0.014	0.040	0.297	0.187
(0,10)	7	-0.014	0.006	0.048	0.688	0.481

Event study results of cluster 70

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	0.010	-0.002	0.047	0.787	0.447
1	13	0.011	0.014	0.047	0.588	0.398
2	13	0.015	0.013	0.043	0.340	0.235
3	13	0.016	0.019	0.043	0.305	0.190
4	13	0.018	0.012	0.044	0.244	0.155
5	13	0.017	0.004	0.039	0.273	0.147
(0,1)	13	0.001	0.000	0.009	0.588	0.668
(0,5)	13	0.007	0.011	0.017	0.146	0.174
(0,10)	13	0.006	0.003	0.018	0.542	0.255

Event study results of cluster 71

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	19	-0.013	-0.011	0.068	0.541	0.424
1	19	-0.020	-0.018	0.065	0.258	0.205
2	19	-0.023	-0.018	0.066	0.210	0.144
3	19	-0.025	-0.018	0.057	0.080	0.071
4	19	-0.022	-0.020	0.057	0.123	0.104
5	19	-0.023	-0.016	0.054	0.104	0.073
(0,1)	19	-0.007	0.000	0.049	0.490	0.558
(0,5)	19	-0.011	0.002	0.055	0.829	0.409
(0,10)	19	0.003	0.003	0.038	0.768	0.762

Event study results of cluster 72

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.033	0.038	0.143	0.813†	0.636
1	5	-0.039	0.036	0.153	0.813†	0.594
2	5	-0.047	0.028	0.156	1.000	0.540
3	5	-0.026	0.038	0.130	0.813†	0.677
4	5	-0.038	0.032	0.145	0.813†	0.586
5	5	-0.045	0.029	0.155	1.000	0.554
(0,1)	5	-0.007	-0.004	0.010	0.188	0.201
(0,5)	5	-0.012	-0.009	0.014	0.125	0.132
(0,10)	5	0.027	0.004	0.065	0.438	0.407

Event study results of cluster 73

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	14	0.057	0.005	0.174	0.391	0.240
1	14	0.060	0.005	0.180	0.326	0.236
2	14	0.062	0.005	0.199	0.358	0.265
3	14	0.063	0.006	0.179	0.268	0.212
4	14	0.064	0.010	0.187	0.217	0.224
5	14	0.068	0.009	0.183	0.135	0.189
(0,1)	14	0.002	0.000	0.019	1.000	0.671
(0,5)	14	0.011	0.011	0.030	0.173	0.208
(0,10)	14	0.003	0.006	0.045	0.952	0.774

Event study results of cluster 74

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	-0.003	-0.011	0.053	0.424	0.865
1	12	-0.003	-0.012	0.052	0.519	0.866
2	12	0.001	-0.011	0.062	0.424	0.964
3	12	-0.002	-0.011	0.048	0.380	0.886
4	12	0.005	-0.011	0.057	0.622	0.757
5	12	0.004	-0.008	0.053	0.677	0.812
(0,1)	12	0.000	-0.001	0.005	0.470	0.977
(0,5)	12	0.006	0.003	0.009	0.007	0.033
(0,10)	12	0.002	0.004	0.032	0.110	0.850

Event study results of cluster 75

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	-0.006	0.019	0.056	1.000	0.795
1	6	0.014	0.032	0.044	0.563	0.479
2	6	0.008	0.024	0.053	0.844	0.725
3	6	0.015	0.034	0.044	0.438	0.438
4	6	0.016	0.041	0.051	0.563	0.481
5	6	0.015	0.028	0.047	0.438	0.463
(0,1)	6	0.020	0.013	0.022	0.031	0.076
(0,5)	6	0.021	0.019	0.014	0.031	0.012
(0,10)	6	0.023	0.025	0.018	0.063	0.024

Event study results of cluster 76

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	-0.008	-0.007	0.018	0.297	0.267
1	7	-0.009	-0.010	0.016	0.219	0.193
2	7	-0.008	-0.002	0.017	0.469	0.228
3	7	-0.015	-0.003	0.030	0.297	0.244
4	7	-0.011	-0.006	0.022	0.219	0.234
5	7	-0.009	-0.009	0.018	0.297	0.205
(0,1)	7	-0.001	-0.001	0.004	0.469	0.578
(0,5)	7	-0.001	-0.003	0.008	0.578	0.676
(0,10)	7	0.004	0.003	0.018	0.688	0.620

Event study results of cluster 77

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	0.008	0.000	0.027	0.733	0.351
1	12	0.008	0.004	0.028	0.470	0.339
2	12	0.007	0.001	0.030	0.677	0.407
3	12	0.008	0.008	0.030	0.233	0.383
4	12	0.006	0.003	0.032	0.339	0.524
5	12	0.008	0.010	0.031	0.339	0.372
(0,1)	12	0.000	0.001	0.007	0.850	0.866
(0,5)	12	0.001	0.001	0.016	0.677	0.877
(0,10)	12	-0.003	0.000	0.016	0.910	0.596

Event study results of cluster 78

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	0.028	0.033	0.024	0.250	0.107
1	4	0.034	0.037	0.023	0.125	0.058†
2	4	0.032	0.032	0.011	0.125	0.010*
3	4	0.025	0.027	0.012	0.125	0.027*
4	4	0.034	0.029	0.015	0.125	0.019*
5	4	0.037	0.035	0.015	0.125	0.015*
(0,1)	4	0.007	0.007	0.006	0.250	0.107
(0,5)	4	0.010	-0.005	0.036	0.875	0.627
(0,10)	4	0.018	0.007	0.041	0.625	0.446

Event study results of cluster 79

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	0.028	0.028	0.052	1.000	0.589
1	2	0.031	0.031	0.055	1.000	0.572
2	2	0.035	0.035	0.051	1.000	0.511
3	2	0.025	0.025	0.053	1.000	0.627
4	2	0.037	0.037	0.041	0.500	0.429
5	2	0.021	0.021	0.050	1.000	0.663
(0,1)	2	0.003	0.003	0.003	0.500	0.380
(0,5)	2	-0.007	-0.007	0.002	0.500	0.109
(0,10)	2	-0.002	-0.002	0.003	1.000	0.562

Event study results of cluster 80

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	6	0.035	0.049	0.039	0.156	0.081†
1	6	0.036	0.049	0.036	0.156	0.058†
2	6	0.030	0.046	0.044	0.219	0.151
3	6	0.033	0.046	0.040	0.156	0.105
4	6	0.033	0.046	0.039	0.156	0.095†
5	6	0.034	0.046	0.038	0.156	0.081†
(0,1)	6	0.001	0.002	0.009	0.844	0.777
(0,5)	6	-0.001	-0.002	0.006	0.688	0.699
(0,10)	6	-0.015	-0.014	0.026	0.438	0.219

Event study results of cluster 81

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	-0.007	-0.010	0.024	0.813	0.551
1	5	-0.015	-0.019	0.029	0.438	0.324
2	5	-0.015	-0.016	0.037	0.625	0.412
3	5	-0.016	-0.017	0.039	0.625	0.425
4	5	-0.019	-0.025	0.046	0.438	0.405
5	5	-0.018	-0.023	0.050	0.438	0.468
(0,1)	5	-0.007	-0.004	0.010	0.188	0.173
(0,5)	5	-0.011	-0.014	0.027	0.438	0.424
(0,10)	5	-0.021	-0.018	0.037	0.313	0.270

Event study results of cluster 82

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	-0.348	0.000	1.167	1.000	0.370
1	10	-0.359	0.003	1.182	0.922	0.362
2	10	-0.368	0.003	1.196	1.000	0.356
3	10	-0.365	0.007	1.171	0.922	0.350
4	10	-0.356	0.005	1.207	1.000	0.375
5	10	-0.350	-0.023	1.138	0.695	0.357
(0,1)	10	-0.011	-0.002	0.025	0.375	0.212
(0,5)	10	-0.001	-0.003	0.062	0.770	0.944
(0,10)	10	-0.010	-0.007	0.052	0.432	0.568

Event study results of cluster 83

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.019	0.014	0.031	0.500	0.397
1	3	0.017	0.014	0.024	0.500	0.330
2	3	0.011	0.014	0.027	0.750	0.545
3	3	0.023	0.022	0.011	0.250	0.063
4	3	0.026	0.031	0.010	0.250	0.048
5	3	0.028	0.026	0.019	0.250	0.130
(0,1)	3	-0.002	0.001	0.007	1.000	0.730
(0,5)	3	0.009	-0.004	0.043	1.000	0.756
(0,10)	3	0.008	-0.005	0.051	1.000	0.804

Event study results of cluster 84

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.001	0.007	0.059	1.000	0.954
1	9	-0.010	-0.011	0.067	0.652	0.675
2	9	-0.004	-0.002	0.048	0.910	0.792
3	9	0.013	-0.007	0.102	0.910	0.710
4	9	0.015	0.009	0.081	0.652	0.590
5	9	0.014	0.005	0.090	0.734	0.656
(0,1)	9	-0.009	-0.009	0.023	0.301	0.298
(0,5)	9	0.015	0.001	0.044	0.570	0.335
(0,10)	9	0.041	0.006	0.120	0.496	0.338

Event study results of cluster 85

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.045	-0.058	0.088	0.375	0.384
1	4	-0.028	-0.042	0.074	0.375	0.500
2	4	-0.047	-0.060	0.079	0.375	0.323
3	4	-0.039	-0.041	0.063	0.375	0.300
4	4	-0.041	-0.048	0.052	0.375	0.215
5	4	-0.035	-0.039	0.041	0.250	0.180
(0,1)	4	0.016	0.010	0.022	0.250	0.234
(0,5)	4	0.009	0.013	0.049	0.875	0.725
(0,10)	4	0.004	0.015	0.070	1.000	0.914

Event study results of cluster 86

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.024	0.032	0.066	0.469	0.366
1	7	0.026	0.033	0.068	0.375	0.350
2	7	0.023	0.033	0.060	0.469	0.352
3	7	0.011	0.014	0.064	0.688	0.658
4	7	0.025	0.026	0.060	0.375	0.318
5	7	0.020	0.034	0.081	0.578	0.535
(0,1)	7	0.002	-0.004	0.019	0.578	0.834
(0,5)	7	-0.004	0.003	0.039	0.938	0.780
(0,10)	7	0.013	0.035	0.039	0.469	0.399

Event study results of cluster 87

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	-0.015	-0.004	0.054	0.469	0.475
1	7	-0.011	0.001	0.053	1.000	0.605
2	7	-0.014	0.002	0.054	0.688	0.533
3	7	-0.008	0.003	0.044	0.813	0.658
4	7	-0.010	0.003	0.049	0.813	0.625
5	7	-0.015	-0.004	0.052	0.813	0.475
(0,1)	7	0.005	0.004	0.006	0.078	0.096
(0,5)	7	0.000	-0.001	0.017	0.688	0.957
(0,10)	7	-0.003	-0.005	0.015	0.469	0.567

Event study results of cluster 88

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	0.107	-0.003	0.221	0.875	0.404
1	4	0.135	0.000	0.272	0.875	0.394
2	4	0.146	0.005	0.284	0.125	0.380
3	4	0.143	0.006	0.278	0.125	0.380
4	4	0.190	0.008	0.368	0.125	0.378
5	4	0.205	0.009	0.398	0.125	0.378
(0,1)	4	0.028	0.003	0.051	0.125	0.352
(0,5)	4	0.098	0.012	0.177	0.125	0.348
(0,10)	4	0.153	0.015	0.277	0.125	0.350

Event study results of cluster 89

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.099	0.014	0.245	0.219	0.324
1	7	0.091	0.015	0.241	0.219	0.354
2	7	0.095	0.015	0.254	0.219	0.361
3	7	0.082	0.011	0.232	0.219	0.388
4	7	0.087	0.013	0.256	0.297	0.403
5	7	0.080	0.009	0.241	0.297	0.414
(0,1)	7	-0.008	-0.002	0.013	0.156	0.159
(0,5)	7	-0.019	-0.009	0.027	0.031	0.102
(0,10)	7	-0.009	-0.010	0.059	0.219	0.701

Event study results of cluster 90

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.104	0.042	0.177	0.027*	0.117
1	9	0.119	0.047	0.195	0.027*	0.103
2	9	0.114	0.048	0.184	0.020*	0.101
3	9	0.121	0.053	0.195	0.012*	0.100
4	9	0.121	0.057	0.181	0.012*	0.080†
5	9	0.129	0.052	0.210	0.074*	0.102
(0,1)	9	0.016	0.005	0.034	0.250	0.206
(0,5)	9	0.026	0.014	0.047	0.164	0.138
(0,10)	9	0.041	0.010	0.100	0.426	0.255

Event study results of cluster 91

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	-0.014	-0.016	0.065	0.383	0.548
1	8	-0.006	-0.011	0.060	0.461	0.772
2	8	-0.004	-0.014	0.065	0.383	0.860
3	8	-0.010	-0.009	0.046	0.547	0.558
4	8	-0.003	-0.010	0.042	0.547	0.838
5	8	-0.005	-0.011	0.041	0.547	0.751
(0,1)	8	0.008	0.004	0.012	0.109	0.107
(0,5)	8	0.010	0.012	0.027	0.461	0.346
(0,10)	8	0.016	0.009	0.053	0.547	0.426

Event study results of cluster 92

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.157	-0.009	0.271	0.652	0.121
1	9	-0.126	-0.006	0.259	0.652	0.184
2	9	-0.134	-0.006	0.263	0.570	0.165
3	9	-0.093	0.019	0.240	0.734	0.279
4	9	-0.079	0.019	0.184	0.652	0.234
5	9	-0.103	0.021	0.231	0.570	0.218
(0,1)	9	0.031	0.005	0.116	0.570	0.440
(0,5)	9	0.054	0.005	0.145	0.426	0.298
(0,10)	9	0.080	0.022	0.194	0.496	0.253

Event study results of cluster 93

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.061	-0.027	0.112	0.055†	0.143
1	9	-0.061	-0.035	0.114	0.055†	0.149
2	9	-0.065	-0.038	0.120	0.055†	0.141
3	9	-0.064	-0.034	0.118	0.055†	0.140
4	9	-0.059	-0.040	0.103	0.055†	0.124
5	9	-0.045	-0.041	0.068	0.074†	0.081
(0,1)	9	0.000	-0.001	0.005	0.820	0.905
(0,5)	9	0.016	0.000	0.051	0.820	0.378
(0,10)	9	0.020	0.001	0.067	0.820	0.390

Event study results of cluster 94

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	7	0.009	0.016	0.101	0.938	0.830
1	7	0.001	0.032	0.091	0.938	0.967
2	7	-0.002	0.009	0.095	1.000	0.959
3	7	0.012	0.038	0.094	0.688	0.752
4	7	-0.008	-0.004	0.079	0.578	0.802
5	7	0.003	-0.015	0.069	0.813	0.913
(0,1)	7	-0.007	-0.004	0.020	0.578	0.388
(0,5)	7	-0.006	-0.006	0.053	0.813	0.792
(0,10)	7	-0.003	0.010	0.087	1.000	0.937

Event study results of cluster 95

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	-0.042	-0.033	0.074	0.160	0.104
1	10	-0.042	-0.032	0.083	0.160	0.147
2	10	-0.046	-0.033	0.086	0.105	0.123
3	10	-0.045	-0.033	0.076	0.084	0.094
4	10	-0.047	-0.035	0.083	0.105	0.107
5	10	-0.046	-0.033	0.090	0.131	0.141
(0,1)	10	0.001	0.002	0.014	0.557	0.885
(0,5)	10	-0.003	0.000	0.020	0.625	0.590
(0,10)	10	-0.005	-0.006	0.022	0.625	0.506

Event study results of cluster 96

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	-0.012	0.015	0.263	0.695	0.886
1	10	0.019	0.012	0.180	0.695	0.741
2	10	0.009	0.011	0.217	0.695	0.901
3	10	0.003	0.012	0.228	0.922	0.968
4	10	0.012	0.014	0.198	0.846	0.855
5	10	0.006	0.003	0.219	0.922	0.932
(0,1)	10	0.032	-0.002	0.107	0.625	0.376
(0,5)	10	0.018	-0.007	0.093	0.492	0.550
(0,10)	10	0.020	0.000	0.120	0.846	0.610

Event study results of cluster 97

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	0.013	0.020	0.035	0.461	0.337
1	8	0.015	0.017	0.035	0.313	0.261
2	8	0.013	0.018	0.029	0.313	0.235
3	8	0.020	0.021	0.034	0.148	0.144
4	8	0.019	0.021	0.027	0.078	0.091
5	8	0.014	0.024	0.040	0.383	0.362
(0,1)	8	0.003	0.001	0.009	0.742	0.437
(0,5)	8	0.001	0.004	0.022	0.945	0.897
(0,10)	8	0.002	0.006	0.021	0.547	0.742

Event study results of cluster 98

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	11	-0.025	-0.018	0.056	0.175	0.171
1	11	-0.021	-0.022	0.043	0.147	0.126
2	11	-0.030	-0.022	0.067	0.175	0.161
3	11	-0.017	-0.008	0.043	0.278	0.228
4	11	-0.028	-0.017	0.068	0.206	0.203
5	11	-0.015	-0.018	0.044	0.278	0.277
(0,1)	11	0.003	0.000	0.021	0.638	0.605
(0,5)	11	0.010	0.007	0.030	0.365	0.310
(0,10)	11	-0.009	-0.004	0.050	0.577	0.570

Event study results of cluster 99

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.044	-0.009	0.076	0.250	0.120
1	9	-0.046	-0.021	0.071	0.203	0.089
2	9	-0.036	-0.017	0.059	0.203	0.110
3	9	-0.037	-0.019	0.058	0.203	0.092
4	9	-0.036	-0.023	0.057	0.203	0.093
5	9	-0.036	-0.023	0.052	0.203	0.074
(0,1)	9	-0.001	-0.002	0.009	0.652	0.673
(0,5)	9	0.009	-0.005	0.034	0.734	0.466
(0,10)	9	0.003	-0.009	0.038	0.570	0.808

Event study results of cluster 100

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	12	-0.015	0.019	0.145	0.233	0.719
1	12	-0.004	0.018	0.123	0.151	0.918
2	12	-0.007	0.017	0.120	0.151	0.846
3	12	-0.009	0.017	0.124	0.380	0.812
4	12	-0.003	0.010	0.093	0.233	0.922
5	12	-0.003	0.019	0.108	0.424	0.918
(0,1)	12	0.012	0.007	0.024	0.151	0.128
(0,5)	12	0.012	0.002	0.048	0.850	0.398
(0,10)	12	0.008	0.004	0.043	0.424	0.528

Event study results of cluster 101

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.040	-0.003	0.129	0.910	0.379
1	9	0.036	-0.011	0.138	0.652	0.455
2	9	0.039	-0.009	0.139	0.820	0.428
3	9	0.055	-0.017	0.188	0.734	0.403
4	9	0.050	-0.018	0.176	0.652	0.423
5	9	0.057	-0.018	0.173	0.910	0.354
(0,1)	9	-0.004	0.001	0.019	0.910	0.553
(0,5)	9	0.017	-0.002	0.053	0.820	0.371
(0,10)	9	0.005	0.002	0.044	0.734	0.768

Event study results of cluster 102

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	17	-0.003	-0.009	0.055	0.782	0.852
1	17	-0.008	-0.009	0.062	0.678	0.587
2	17	-0.005	-0.002	0.065	0.818	0.770
3	17	0.007	0.001	0.058	0.782	0.617
4	17	0.001	-0.008	0.065	0.890	0.952
5	17	0.008	0.010	0.063	0.459	0.619
(0,1)	17	-0.006	-0.004	0.020	0.263	0.250
(0,5)	17	0.010	0.011	0.023	0.109	0.090
(0,10)	17	-0.006	-0.001	0.034	0.306	0.508

Event study results of cluster 103

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	13	-0.003	-0.012	0.044	0.414	0.836
1	13	0.004	-0.003	0.059	0.787	0.816
2	13	0.007	-0.002	0.065	0.787	0.706
3	13	0.012	-0.006	0.072	0.839	0.559
4	13	0.011	-0.010	0.066	0.946	0.559
5	13	0.009	-0.005	0.068	0.946	0.627
(0,1)	13	0.007	0.002	0.019	0.455	0.251
(0,5)	13	0.012	0.003	0.028	0.168	0.149
(0,10)	13	0.011	0.007	0.031	0.146	0.230

Event study results of cluster 104

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.071	-0.050	0.122	0.375	0.330
1	4	-0.043	-0.021	0.099	0.625	0.452
2	4	-0.070	-0.050	0.111	0.375	0.297
3	4	-0.067	-0.047	0.116	0.375	0.333
4	4	-0.087	-0.069	0.122	0.250	0.246
5	4	-0.071	-0.045	0.126	0.625	0.340
(0,1)	4	0.028	0.029	0.024	0.250	0.103
(0,5)	4	0.000	-0.005	0.034	1.000	0.995
(0,10)	4	-0.007	-0.007	0.037	0.625	0.742

Event study results of cluster 105

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	0.007	0.015	0.061	0.750	0.856
1	3	0.000	0.011	0.060	1.000	0.999
2	3	-0.002	0.020	0.058	1.000	0.963
3	3	0.005	0.019	0.056	1.000	0.900
4	3	-0.001	0.019	0.059	1.000	0.987
5	3	0.004	0.022	0.066	1.000	0.926
(0,1)	3	-0.007	-0.007	0.003	0.250	0.053
(0,5)	3	-0.003	-0.005	0.010	0.750	0.615
(0,10)	3	-0.006	-0.002	0.020	0.750	0.641

Event study results of cluster 106

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	5	0.070	0.045	0.064	0.063†	0.070†
1	5	0.068	0.052	0.069	0.063†	0.091†
2	5	0.076	0.051	0.078	0.063†	0.095†
3	5	0.057	0.050	0.060	0.125	0.098†
4	5	0.057	0.061	0.052	0.125	0.072†
5	5	0.059	0.064	0.058	0.125	0.086†
(0,1)	5	-0.002	0.002	0.008	0.813	0.617
(0,5)	5	-0.011	-0.012	0.024	0.438	0.352
(0,10)	5	-0.030	-0.003	0.068	0.625	0.379

Event study results of cluster 107

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	10	0.124	-0.006	0.255	0.492	0.158
1	10	0.136	-0.011	0.278	0.492	0.158
2	10	0.118	-0.007	0.260	0.492	0.184
3	10	0.118	-0.008	0.260	0.492	0.185
4	10	0.112	-0.004	0.240	0.492	0.176
5	10	0.119	-0.004	0.241	0.492	0.152
(0,1)	10	0.011	0.001	0.033	0.922	0.298
(0,5)	10	-0.005	0.005	0.052	0.557	0.771
(0,10)	10	0.006	0.011	0.121	0.193	0.877

Event study results of cluster 108

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	-0.014	-0.014	0.010	0.500	0.299
1	2	-0.013	-0.013	0.013	0.500	0.392
2	2	-0.019	-0.019	0.004	0.500	0.098
3	2	-0.017	-0.017	0.004	0.500	0.091
4	2	-0.019	-0.019	0.008	0.500	0.177
5	2	-0.027	-0.027	0.004	0.500	0.070
(0,1)	2	0.001	0.001	0.022	1.000	0.949
(0,5)	2	-0.013	-0.013	0.014	0.500	0.417
(0,10)	2	-0.018	-0.018	0.015	0.500	0.343

Event study results of cluster 109

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	0.025	0.025	0.031	0.500	0.453
1	2	0.030	0.030	0.038	0.500	0.465
2	2	0.032	0.032	0.039	0.500	0.458
3	2	0.024	0.024	0.029	0.500	0.446
4	2	0.030	0.030	0.037	0.500	0.458
5	2	0.018	0.018	0.021	0.500	0.426
(0,1)	2	0.005	0.005	0.007	1.000	0.526
(0,5)	2	-0.007	-0.007	0.010	1.000	0.515
(0,10)	2	-0.007	-0.007	0.010	1.000	0.519

Event study results of cluster 110

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.008	0.001	0.063	0.820	0.720
1	9	0.017	0.001	0.084	0.734	0.566
2	9	0.013	0.009	0.068	0.570	0.575
3	9	0.016	0.007	0.073	0.426	0.532
4	9	0.022	0.016	0.077	0.359	0.419
5	9	0.029	0.011	0.095	0.359	0.393
(0,1)	9	0.009	0.002	0.024	0.426	0.292
(0,5)	9	0.021	0.013	0.040	0.039	0.157
(0,10)	9	0.013	0.016	0.066	0.426	0.571

Event study results of cluster 112

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	0.008	0.001	0.063	0.820	0.720
1	9	0.017	0.001	0.084	0.734	0.566
2	9	0.013	0.009	0.068	0.570	0.575
3	9	0.016	0.007	0.073	0.426	0.532
4	9	0.022	0.016	0.077	0.359	0.419
5	9	0.029	0.011	0.095	0.359	0.393
(0,1)	9	0.009	0.002	0.024	0.426	0.292
(0,5)	9	0.021	0.013	0.040	0.039	0.157
(0,10)	9	0.013	0.016	0.066	0.426	0.571

Event study results of cluster 113

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	2	0.026	0.026	0.101	1.000	0.781
1	2	0.027	0.027	0.113	1.000	0.794
2	2	0.024	0.024	0.111	1.000	0.810
3	2	0.019	0.019	0.122	1.000	0.860
4	2	0.018	0.018	0.112	1.000	0.857
5	2	0.020	0.020	0.119	1.000	0.855
(0,1)	2	0.001	0.001	0.012	1.000	0.911
(0,5)	2	-0.006	-0.006	0.018	1.000	0.715
(0,10)	2	-0.015	-0.015	0.003	0.500	0.086

Event study results of cluster 114

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	0.000	0.014	0.044	1.000	0.998
1	4	-0.010	0.005	0.056	1.000	0.734
2	4	-0.003	0.011	0.054	1.000	0.919
3	4	-0.004	0.004	0.058	1.000	0.891
4	4	-0.009	-0.005	0.045	0.875	0.723
5	4	-0.015	-0.014	0.069	0.625	0.688
(0,1)	4	-0.011	-0.009	0.017	0.625	0.312
(0,5)	4	-0.015	0.001	0.068	1.000	0.684
(0,10)	4	-0.006	-0.006	0.072	0.875	0.870

Event study results of cluster 115

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.030	-0.021	0.044	0.074†	0.078†
1	9	-0.028	-0.019	0.044	0.055†	0.096†
2	9	-0.024	-0.026	0.044	0.164	0.136
3	9	-0.021	-0.025	0.049	0.203	0.225
4	9	-0.016	-0.021	0.049	0.250	0.348
5	9	-0.008	-0.016	0.055	0.496	0.680
(0,1)	9	0.002	0.001	0.011	0.734	0.567
(0,5)	9	0.022	0.022	0.033	0.098	0.084
(0,10)	9	0.021	0.006	0.040	0.203	0.156

Event study results of cluster 116

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	8	-0.038	-0.004	0.148	0.742	0.493
1	8	-0.050	-0.005	0.167	0.742	0.427
2	8	-0.069	-0.009	0.207	0.461	0.376
3	8	-0.073	-0.018	0.204	0.383	0.349
4	8	-0.059	-0.011	0.172	0.461	0.367
5	8	-0.072	-0.010	0.196	0.383	0.331
(0,1)	8	-0.012	-0.001	0.024	0.383	0.204
(0,5)	8	-0.035	-0.022	0.055	0.039	0.120
(0,10)	8	-0.126	-0.015	0.322	0.250	0.306

Event study results of cluster 117

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	11	-0.005	0.000	0.033	0.638	0.611
1	11	-0.006	0.000	0.035	0.638	0.557
2	11	-0.014	0.000	0.042	0.320	0.281
3	11	-0.009	-0.001	0.035	0.520	0.423
4	11	-0.011	0.003	0.041	0.520	0.372
5	11	-0.009	-0.007	0.038	0.465	0.426
(0,1)	11	-0.001	0.000	0.005	1.000	0.471
(0,5)	11	-0.004	-0.008	0.013	0.320	0.324
(0,10)	11	-0.010	-0.014	0.016	0.102	0.070

Event study results of cluster 118

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	4	-0.076	-0.065	0.082	0.125	0.162
1	4	-0.075	-0.067	0.078	0.125	0.151
2	4	-0.070	-0.068	0.075	0.125	0.160
3	4	-0.059	-0.047	0.065	0.125	0.167
4	4	-0.063	-0.050	0.071	0.125	0.172
5	4	-0.071	-0.058	0.080	0.125	0.175
(0,1)	4	0.001	-0.002	0.007	1.000	0.872
(0,5)	4	0.005	0.005	0.004	0.125	0.075
(0,10)	4	0.029	0.023	0.033	0.250	0.173

Event study results of cluster 119

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	3	-0.018	-0.018	0.002	0.250	0.005**
1	3	-0.020	-0.021	0.003	0.250	0.008**
2	3	-0.020	-0.023	0.004	0.250	0.014*
3	3	-0.022	-0.025	0.006	0.250	0.022**
4	3	-0.029	-0.031	0.006	0.250	0.015*
5	3	-0.022	-0.025	0.007	0.250	0.030*
(0,1)	3	-0.002	-0.002	0.001	0.250	0.066†
(0,5)	3	-0.005	-0.007	0.005	0.500	0.227
(0,10)	3	-0.006	-0.012	0.013	0.500	0.485

Event study results of cluster 120

Event Day(s)	N	Mean	Median	Stand deviation	WSR p-Value	t-test p-Value
0	9	-0.018	0.004	0.104	0.250	0.613
1	9	-0.016	0.006	0.094	0.203	0.613
2	9	-0.013	0.006	0.093	0.164	0.694
3	9	-0.010	0.009	0.080	0.203	0.728
4	9	-0.016	0.005	0.099	0.301	0.634
5	9	-0.012	0.009	0.086	0.250	0.683
(0,1)	9	0.002	0.000	0.012	0.652	0.656
(0,5)	9	0.006	0.000	0.020	0.820	0.371
(0,10)	9	-0.004	-0.002	0.015	0.652	0.388

REFERENCES

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On Making Causal Claims: A Review and Recommendations. *The Leadership Quarterly*, *21*(6), 1086-1120.

Arevalo, J. A., & Aravind, D. (2017). Strategic Outcomes in Voluntary Csr: Reporting Economic and Reputational Benefits in Principles-Based Initiatives. *Journal of Business Ethics*, *144*(1), 201-217.

Arora, P., Hora, M., Singhal, V., & Subramanian, R. (2020). When Do Appointments of Corporate Sustainability Executives Affect Shareholder Value? *Journal of Operations Management*, *66*(4), 464-487.

Ba, S., Lisic, L. L., Liu, Q., & Stallaert, J. (2013). Stock Market Reaction to Green Vehicle Innovation. *Production and Operations Management*, *22*(4), 976-990.

Bae, S. M., Masud, M., Kaium, A., & Kim, J. D. (2018). A Cross-Country Investigation of Corporate Governance and Corporate Sustainability Disclosure: A Signaling Theory Perspective. *Sustainability*, *10*(8), 2611.

Balboa, M., & Martí, J. (2007). Factors That Determine the Reputation of Private Equity Managers in Developing Markets. *Journal of Business Venturing*, *22*(4), 453-480.

Barber, B. M., & Lyon, J. D. (1996). Detecting Abnormal Operating Performance: The Empirical Power and Specification of Test Statistics. *Journal of Financial Economics*, *41*(3), 359-399.

Bartov, E., Givoly, D., & Hayn, C. (2002). The Rewards to Meeting or Beating Earnings Expectations. *Journal of Accounting and Economics*, *33*(2), 173-204.

Bauman, K., & Tuzhilin, A. (2022). Know Thy Context: Parsing Contextual Information from User Reviews for Recommendation Purposes. *Information Systems Research*, *33*(1), 179-202.

Belkhir, L., Sneha, B., & Samih, A. (2017). Does GRI Reporting Impact Environmental Sustainability? A Cross-Industry Analysis of Co2 Emissions Performance between GRI-Reporting and Non-Reporting Companies. *Management of Environmental Quality: An International Journal*, *28*(2), 138-155.

Belsley, D. A. (1980). On the Efficient Computation of the Nonlinear Full-Information Maximum-Likelihood Estimator. *Journal of Econometrics*, *14*(2), 203-225.

Ben-Jebara, M., & Modi, S. B. (2021). Product Personalization and Firm Performance: An Empirical Analysis of the Pharmaceutical Industry. *Journal of Operations Management*, *67*(1), 82-104.

Bernard, S., Abdelgadir, S., & Belkhir, L. (2015). Does GRI Reporting Impact Environmental Sustainability? An Industry-Specific Analysis of Co2 Emissions Performance between Reporting and Non-Reporting Companies. *Journal of Sustainable Development*, *8*(9), 190-205.

Bird, R. B., Smith, E., Alvard, M., Chibnik, M., Cronk, L., Giordani, L., Hagen, E., Hammerstein, P., & Neiman, F. (2005). Signaling Theory, Strategic Interaction, and Symbolic Capital. *Current Anthropology*, *46*(2), 221-248.

Brandon-Jones, E., Dutordoir, M., Frota Neto, J. Q., & Squire, B. (2017). The Impact of Reshoring Decisions on Shareholder Wealth. *Journal of Operations Management*, *49-51*, 31-36.

Brown, H. S., de Jong, M., & Lessidrenska, T. (2009). The Rise of the Global Reporting Initiative: A Case of Institutional Entrepreneurship. *Environmental Politics*, *18*(2), 182-200.

Brown, H. S., de Jong, M., & Levy, D. L. (2009). Building Institutions Based on Information Disclosure: Lessons from GRI's Sustainability Reporting. *Journal of Cleaner Production*, *17*(6), 571-580.

BSR. (2010). *Walmart: Improving Supplier Energy Efficiency*. Retrieved July 14 from https://www.bsr.org/en/our-insights/case-study-view/walmart-improving-supplier-energy-efficiency

Buallay, A. (2019). Is Sustainability Reporting (ESG) Associated with Performance? Evidence from the European Banking Sector. *Management of Environmental Quality: An International Journal*, *30*(1), 98-115.

Bustos, O., & Pomares-Quimbaya, A. (2020). Stock Market Movement Forecast: A Systematic Review. *Expert Systems with Applications*, *156*, 113464.

Cantor, D. E., Morrow, P. C., & Montabon, F. (2012). Engagement in Environmental Behaviors among Supply Chain Management Employees: An Organizational Support Theoretical Perspective. *Journal of Supply Chain Management*, *48*(3), 33-51.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57-82.

Chatterjee, D., Richardson, V. J., & Zmud, R. W. (2001). Examining the Shareholder Wealth Effects of Announcements of Newly Created CIO Positions. *MIS Quarterly*, 43-70.

Chen, L., Feldmann, A., & Tang, O. (2015). The Relationship between Disclosures of Corporate Social Performance and Financial Performance: Evidences from GRI Reports in Manufacturing Industry. *International Journal of Production Economics*, *170*, 445-456.

Chen, S., & Bouvain, P. (2009). Is Corporate Responsibility Converging? A Comparison of Corporate Responsibility Reporting in the USA, UK, Australia, and Germany. *Journal of Business Ethics*, *87*(1), 299-317.

Chen, Y., Ganesan, S., & Liu, Y. (2009). Does a Firm's Product-Recall Strategy Affect Its Financial Value? An Examination of Strategic Alternatives During Product-Harm Crises. *Journal of Marketing*, *73*(6), 214-226.

Ching, H. Y., & Gerab, F. (2017). Sustainability Reports in Brazil through the Lens of Signaling, Legitimacy and Stakeholder Theories. *Social Responsibility Journal*, *13*(1), 95-110.

Ching, H. Y., Gerab, F., & Toste, T. H. (2017). The Quality of Sustainability Reports and Corporate Financial Performance: Evidence from Brazilian Listed Companies. *SAGE Open*, *7*(2), 1–9.

Chiu, S.-C., Lin, H.-C., & Wang, C.-S. (2017). The Impact of Investments in Pollution Reduction on Shareholder Wealth: Evidence from Taiwanese Manufacturing Companies. *Corporate Social Responsibility and Environmental Management*, *24*(6), 676-691.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, *37*(1), 39-67.

Corbett, C. J., Montes-Sancho, M. J., & Kirsch, D. A. (2005). The Financial Impact of Iso 9000 Certification in the United States: An Empirical Analysis. *Management Science*, *51*(7), 1046-1059.

Cowan, A. R. (1992). Nonparametric Event Study Tests. *Review of Quantitative Finance and Accounting*, *2*(4), 343-358.

Cuadrado-Ballesteros, B., Garcia-Sanchez, I.-M., & Ferrero, J. M. (2016). How Are Corporate Disclosures Related to the Cost of Capital? The Fundamental Role of Information Asymmetry. *Management Decision*, *54*(7), 1669-1701.

Dam, L., & Petkova, B. (2014). The Impact of Environmental Supply Chain Sustainability Programs on Shareholder Wealth. *International Journal of Operations & Production Management*.

Delmas, M., & Montiel, I. (2008). The Diffusion of Voluntary International Management Standards: Responsible Care, ISO 9000, and ISO 14001 in the Chemical Industry. *Policy Studies Journal*, *36*(1), 65-93.

Ding, L., Lam, H. K. S., Cheng, T. C. E., & Zhou, H. (2018). A Review of Short-Term Event Studies in Operations and Supply Chain Management. *International Journal of Production Economics*, *200*, 329-342.

Ding, Q., Wu, S., Sun, H., Guo, J., & Guo, J. (2020). Hierarchical Multi-Scale Gaussian Transformer for Stock Movement Prediction. *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence Special Track on AI in FinTech.*

Ding, X., Zhang, Y., Liu, T., & Duan, J. (2014). Using Structured Events to Predict Stock Price Movement: An Empirical Investigation. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP),*

Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015). Deep Learning for Event-Driven Stock Prediction. *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence.*

Dorr, B. J., Petrovic, M., Allen, J. F., Teng, C. M., & Dalton, A. (2014). Discovering and Characterizing Emerging Events in Big Data. *Proceedings of the AAAI Fall Symposium Natural Language Access to Big Data.*

Du, X., & Tanaka-Ishii, K. (2020). Stock Embeddings Acquired from News Articles and Price History, and an Application to Portfolio Optimization. *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics.*

Duan, J., Zhang, Y., Ding, X., Chang, C. Y., & Liu, T. (2018). Learning Target-Specific Representations of Financial News Documents for Cumulative Abnormal Return Prediction. *Proceedings of the 27th International Conference on Computational Linguistics.*

Eftekhar, M., Li, H., Van Wassenhove, L. N., & Webster, S. (2017). The Role of Media Exposure on Coordination in the Humanitarian Setting. *Production and Operations Management*, *26*(5), 802-816.

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived Organizational Support. *Journal of Applied Psychology*, *71*(3), 500-507.

Elberse, A. (2007). The Power of Stars: Do Star Actors Drive the Success of Movies? *Journal of Marketing*, *71*(4), 102-120.

Fama, E. F., Fisher, L., Jensen, M., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, *10*(1), 1-21.

Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Fan, D., Liang, T., Yeung, A. C., & Zhang, H. (2020). The Impact of Capacity-Reduction Initiatives on the Stock Market Value of Chinese Manufacturing Firms. *International Journal of Production Economics*, *223*, 107533.

Fan, D., Lo, C. K. Y., Yeung, A. C. L., & Cheng, T. C. E. (2018). The Impact of Corporate Label Change on Long-Term Labor Productivity. *Journal of Business Research*, *86*, 96-108.

Feng, Y., Lai, K.-h., & Zhu, Q. (2020). Legitimacy in Operations: How Sustainability Certification Announcements by Chinese Listed Enterprises Influence Their Market Value? *International Journal of Production Economics*, *224*, 107563.

Feng, Y., & Shah, C. (2022). Unifying Telescope and Microscope: A Multi-Lens Framework with Open Data for Modeling Emerging Events. *Information Processing & Management*, *59*(2), 102811.

Fernandez-Feijoo, B., Romero, S., & Ruiz, S. (2014). Effect of Stakeholders' Pressure on Transparency of Sustainability Reports within the GRI Framework. *Journal of Business Ethics*, *122*(1), 53-63.

Ferreira Quilice, T., Oranges Cezarino, L., Fernandes Rodrigues Alves, M., Bartocci Liboni, L., & Ferreira Caldana, A. C. (2018). Positive and Negative Aspects of GRI Reporting as Perceived by Brazilian Organizations. *Environmental Quality Management*, *27*(3), 19-30.

Flammer, C. (2015). Does Corporate Social Responsibility Lead to Superior Financial Performance? A Regression Discontinuity Approach. *Management Science*, *61*(11), 2549-2568.

Flammer, C., Toffel, M. W., & Viswanathan, K. (2019). Shareholder Activism and Firms' Voluntary Disclosure of Climate Change Risks. *Available at SSRN*.

Forbes. (2019). *Strategy in a Volatile World*. Retrieved August 1 from https://www.forbes.com/sites/jeroenkraaijenbrink/2019/01/11/strategy-in-a-volatile-world/?sh=1670a6da4220

Gao, H., Darroch, J., Mather, D., & MacGregor, A. (2008). Signaling Corporate Strategy in IPO Communication: A Study of Biotechnology Ipos on the Nasdaq. *The Journal of Business Communication (1973)*, *45*(1), 3-30.

Ge, C., Huang, H., Wang, Z., Jiang, J., & Liu, C. (2022). Working from Home and Firm Resilience to the Covid-19 Pandemic. *Journal of Operations Management*, 1-27.

Girotra, K., Terwiesch, C., & Ulrich, K. T. (2007). Valuing R&D Projects in a Portfolio: Evidence from the Pharmaceutical Industry. *Management Science*, *53*(9), 1452-1466.

Goel, R., & Cragg, W. (2005). *Guide to Instruments of Corporate Responsibility: An Overview of 16 Key Tools for Labour Fund Trustees*. Schulich School of Business.

Governance & Accountability Institute. (2020). *Governance & Accountability Institute: Flash Report Russell 2020*. https://www.globenewswire.com/news-release/2020/07/16/2063434/0/en/90-of-S-P-500-Index-Companies-Publish-Sustainability-Reports-in-2019-G-A-Announces-in-its-Latest-Annual-2020-Flash-Report.html

Greene, W. H. (2003). *Econometric Analysis*. Pearson Education India.

Grewal, J., Riedl, E. J., & Serafeim, G. (2019). Market Reaction to Mandatory Nonfinancial Disclosure. *Management Science*, *65*(7), 3061-3084.

GRI. (2020). *GRI's Mission and History*. Retrieved July 11 from https://www.globalreporting.org/about-gri/mission-history/

Hardcopf, R., Shah, R., & Dhanorkar, S. (2021). The Impact of a Spill or Pollution Accident on Firm Environmental Activity: An Empirical Investigation. *Production and Operations Management*, *30*(8), 2467-2491.

Hardeniya, N. (2015). *Nltk Essentials*. Packt Publishing.

Hardeniya, N., Perkins, J., Chopra, D., Joshi, N., & Mathur, I. (2016). *Natural Language Processing: Python and Nltk*. Packt Publishing Ltd.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica: Journal of the Econometric Society*, 153-161.

Hendricks, K. B., Hora, M., & Singhal, V. R. (2015). An Empirical Investigation on the Appointments of Supply Chain and Operations Management Executives. *Management Science*, *61*(7), 1562-1583.

Hendricks, K. B., & Singhal, V. R. (1996). Quality Awards and the Market Value of the Firm: An Empirical Investigation. *Management Science*, *42*(3), 415-436.

Hendricks, K. B., & Singhal, V. R. (1997). Delays in New Product Introductions and the Market Value of the Firm: The Consequences of Being Late to the Market. *Management Science*, *43*(4), 422-436.

Hendricks, K. B., & Singhal, V. R. (2003). The Effect of Supply Chain Glitches on Shareholder Wealth. *Journal of Operations Management*, *21*(5), 501-522.

Hendricks, K. B., Singhal, V. R., & Wiedman, C. I. (1995). The Impact of Capacity Expansion on the Market Value of the Firm. *Journal of Operations Management*, *12*(3-4), 259-272.

Hendricks, K. B., Singhal, V. R., & Zhang, R. (2009). The Effect of Operational Slack, Diversification, and Vertical Relatedness on the Stock Market Reaction to Supply Chain Disruptions. *Journal of Operations Management*, *27*(3), 233-246.

Homburg, C., Vollmayr, J., & Hahn, A. (2014). Firm Value Creation through Major Channel Expansions: Evidence from an Event Study in the United States, Germany, and China. *Journal of Marketing*, *78*(3), 38-61.

IBM. (2021). *Find Your Essential: How to Thrive in a Post-Pandemic Reality*. Retrieved Aug 13 from https://www.ibm.com/downloads/cas/WVPWGPYE.

Jacobs, B. W. (2014). Shareholder Value Effects of Voluntary Emissions Reduction. *Production and Operations Management*, *23*(11), 1859-1874.

Jacobs, B. W., & Singhal, V. R. (2014). The Effect of Product Development Restructuring on Shareholder Value. *Production and Operations Management*, *23*(5), 728-743.

Jacobs, B. W., & Singhal, V. R. (2017). The Effect of the Rana Plaza Disaster on Shareholder Wealth of Retailers: Implications for Sourcing Strategies and Supply Chain Governance. *Journal of Operations Management*, *49-51*, 52-66.

Jacobs, B. W., & Singhal, V. R. (2020). Shareholder Value Effects of the Volkswagen Emissions Scandal on the Automotive Ecosystem. *Production and Operations Management*, *29*(10), 2230-2251.

Jacobs, B. W., Singhal, V. R., & Subramanian, R. (2010). An Empirical Investigation of Environmental Performance and the Market Value of the Firm. *Journal of Operations Management*, *28*(5), 430-441.

Janney, J. J., & Folta, T. B. (2003). Signaling through Private Equity Placements and Its Impact on the Valuation of Biotechnology Firms. *Journal of Business Venturing*, *18*(3), 361-380.

Janney, J. J., & Folta, T. B. (2006). Moderating Effects of Investor Experience on the Signaling Value of Private Equity Placements. *Journal of Business Venturing*, *21*(1), 27-44.

Jones, K. S. (1972). A Statistical Interpretation of Term Specificity and Its Application in Retrieval. *Journal of Documentation*, 28(5), 111-121.

Ketokivi, M., & McIntosh, C. N. (2017). Addressing the Endogeneity Dilemma in Operations Management Research: Theoretical, Empirical, and Pragmatic Considerations. *Journal of Operations Management*, *52*, 1-14.

Klassen, R. D. (1993). The Integration of Environmental Issues into Manufacturing. *Production and Inventory Management Journal*, *34*(1), 82-88.

Klassen, R. D., & McLaughlin, C. P. (1996). The Impact of Environmental Management on Firm Performance. *Management Science*, *42*(8), 1199-1214.

Ko, D.-G., Mai, F., Shan, Z., & Zhang, D. (2019). Operational Efficiency and Patient-Centered Health Care: A View from Online Physician Reviews. *Journal of Operations Management*, *65*(4), 353-379.

Kolk, A., & Perego, P. (2010). Determinants of the Adoption of Sustainability Assurance Statements: An International Investigation. *Business Strategy and the Environment*, *19*(3), 182-198.

Konchitchki, Y., & O'Leary, D. E. (2011). Event Study Methodologies in Information Systems Research. *International Journal of Accounting Information Systems*, *12*(2), 99-115.

KPMG. (2017). *The Kpmg Survey of Corporate Responsibility Reporting*. https://cifal-flanders.org/wp-content/uploads/2018/12/Mike-Boonen_Non-Financial-Reporting_ENG_05-02-2019.pdf

Lam, H. K., Yeung, A. C., Cheng, T., & Humphreys, P. K. (2016). Corporate Environmental Initiatives in the Chinese Context: Performance Implications and Contextual Factors. *International Journal of Production Economics*, *180*, 48-56.

Lee, J., & Maxfield, S. (2015). Doing Well by Reporting Good: Reporting Corporate Responsibility and Corporate Performance. *Business and Society Review*, *120*(4), 577-606.

Leone, A. J., Li, E. X., & Liu, M. (2021). On the SEC's 2010 Enforcement Cooperation Program. *Journal of Accounting and Economics*, *71*(1), 101355.

Lerner, J. S., & Tetlock, P. E. (1994). Accountability and Social Cognition. *Encyclopedia of Human Behavior*, *1*, 3098-3121.

Li, H., Lam, H. K. S., Ho, W., & Yeung, A. C. L. (2022). The Impact of Chief Risk Officer Appointments on Firm Risk and Operational Efficiency. *Journal of Operations Management*, *68*(3), 241-269.

Liang, X., Chen, R.-C., He, Y., & Chen, Y. (2013). Associating Stock Prices with Web Financial Information Time Series Based on Support Vector Regression. *Neurocomputing*, *115*, 142-149.

Liu, L. X., Sherman, A. E., & Zhang, Y. (2014). The Long-Run Role of the Media: Evidence from Initial Public Offerings. *Management Science*, *60*(8), 1945-1964.

Liu, Y., Li, Z., Xiong, H., Gao, X., & Wu, J. (2010). Understanding of Internal Clustering Validation Measures. 2010 IEEE International Conference on Data Mining.

Liu, Y., Li, Z., Xiong, H., Gao, X., Wu, J., & Wu, S. (2013). Understanding and Enhancement of Internal Clustering Validation Measures. *IEEE Transactions on Cybernetics*, *43*(3), 982-994.

Lo, C. K. Y., Pagell, M., Fan, D., Wiengarten, F., & Yeung, A. C. L. (2014). OHSAS 18001 Certification and Operating Performance: The Role of Complexity and Coupling. *Journal of Operations Management*, *32*(5), 268-280.

Lo, C. K. Y., Tang, C. S., Zhou, Y., Yeung, A. C. L., & Fan, D. (2018). Environmental Incidents and the Market Value of Firms: An Empirical Investigation in the Chinese Context. *Manufacturing & Service Operations Management*, *20*(3), 422-439.

Loh, L., Thomas, T., & Wang, Y. (2017). Sustainability Reporting and Firm Value: Evidence from Singapore-Listed Companies. *Sustainability*, *9*(11), 2112.

Longoni, A., Pagell, M., Shevchenko, A., & Klassen, R. (2019). Human Capital Routines and Sustainability Trade-Offs: The Influence of Conflicting Schemas for Operations and Safety Managers. *International Journal of Operations & Production Management*, *39*(5), 690-713.

Luo, X., & Bhattacharya, C. B. (2006). Corporate Social Responsibility, Customer Satisfaction, and Market Value. *Journal of Marketing*, *70*(4), 1-18.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, *35*(1), 13-39.

Manning, C. D., Surdeanu, M., Bauer, J., Finkel, J. R., Bethard, S., & McClosky, D. (2014). The Stanford Corenlp Natural Language Processing Toolkit. Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations.

Martínez-Ferrero, J., & García-Sánchez, I.-M. (2017). Coercive, Normative and Mimetic Isomorphism as Determinants of the Voluntary Assurance of Sustainability Reports. *International Business Review*, *26*(1), 102-118.

McDermott, G. A., Corredoira, R. A., & Kruse, G. (2009). Public-Private Institutions as Catalysts of Upgrading in Emerging Market Societies. *Academy of Management Journal*, *52*(6), 1270-1296.

McKinsey. (2022). *Does ESG Really Matter—and Why?* Retrieved 22 Dec from https://www.mckinsey.com/capabilities/sustainability/our-insights/does-esg-really-matter-and-why

Mollenkopf, D. A., Peinkofer, S. T., & Chu, Y. (2022). Supply Chain Transparency: Consumer Reactions to Incongruent Signals. *Journal of Operations Management*, *68*(4), 306-327.

Montgomery, C. A., & Wernerfelt, B. (1988). Diversification, Ricardian Rents, and Tobin's Q. *The Rand Journal of Economics*, 623-632.

Orzes, G., Jia, F., Sartor, M., & Nassimbeni, G. (2017). Performance Implications of Sa8000 Certification. *International Journal of Operations & Production Management*, 37(11), 37(11), 1625-1653.

Orzes, G., Moretto, A. M., Moro, M., Rossi, M., Sartor, M., Caniato, F., & Nassimbeni, G. (2020). The Impact of the United Nations Global Compact on Firm

Performance: A Longitudinal Analysis. *International Journal of Production Economics*, *227*, 107664.

Pagell, M., Klassen, R., Johnston, D., Shevchenko, A., & Sharma, S. (2015). Are Safety and Operational Effectiveness Contradictory Requirements: The Roles of Routines and Relational Coordination. *Journal of Operations Management*, *36*, 1-14.

Panwar, R., & Suddaby, R. (2021). Managing Transparency: Non-Financial Disclosure and the Responsible Corporation [Special Issue]. *California Management Review*.

Park, N. K., & Mezias, J. M. (2005). Before and after the Technology Sector Crash: The Effect of Environmental Munificence on Stock Market Response to Alliances of E-Commerce Firms. *Strategic Management Journal*, *26*(11), 987-1007.

Pérez-López, D., Moreno-Romero, A., & Barkemeyer, R. (2015). Exploring the Relationship between Sustainability Reporting and Sustainability Management Practices. *Business Strategy and the Environment*, *24*(8), 720-734.

PureStrategies. (2021). *Walmart: Embedding Sustainability in a Vast Supply Chain*. Retrieved July 8 from https://purestrategies.com/case-study/walmart-embedding-sustainability-in-a-vast-supply-chain

Qin, Y., Song, D., Chen, H., Cheng, W., Jiang, G., & Cottrell, G. (2017). A Dual-Stage Attention-Based Recurrent Neural Network for Time Series Prediction. *arXiv preprint arXiv:1704.02971*.

Qiu, Y., & Kahn, M. E. (2018). Better Sustainability Assessment of Green Buildings with High-Frequency Data. *Nature Sustainability*, *1*(11), 642-649.

Robinson, M., Kleffner, A., & Bertels, S. (2011). Signaling Sustainability Leadership: Empirical Evidence of the Value of Djsi Membership. *Journal of Business Ethics*, *101*(3), 493-505.

Rousseeuw, P. J. (1987). Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics*, *20*, 53-65.

Ruiz, E. J., Hristidis, V., Castillo, C., Gionis, A., & Jaimes, A. (2012). Correlating Financial Time Series with Micro-Blogging Activity. Proceedings of the fifth ACM International Conference on Web Search and Data Mining.

Salton, G., & Buckley, C. (1988). Term-Weighting Approaches in Automatic Text Retrieval. *Information Processing & Management*, *24*(5), 513-523.

Schadewitz, H., & Niskala, M. (2010). Communication Via Responsibility Reporting and Its Effect on Firm Value in Finland. *Corporate Social Responsibility and Environmental Management*, *17*(2), 96-106.

Scholes, M., & Williams, J. (1977). Estimating Betas from Nonsynchronous Data. *Journal of Financial Economics*, *5*(3), 309-327.

Schumaker, R. P., & Chen, H. (2009). Textual Analysis of Stock Market Prediction Using Breaking Financial News: The Azfin Text System. *ACM Transactions on Information Systems (TOIS)*, *27*(2), 1-19.

Scott, A., Li, M., Cantor, D. E., & Corsi, T. M. (2022). Do Voluntary Environmental Programs Matter? Evidence from the Epa Smartway Program. *Journal of Operations Management*, 69(2), 284-304.

Siegel, D. S. (2009). Green Management Matters Only If It Yieds More Green: An Economic/Strategic Perspective. *Academy of Management Perspectives*, *23*(3), 5-16.

Spence, M. (2002). Signaling in Retrospect and the Informational Structure of Markets. *American Economic Review*, *92*(3), 434-459.

Stiglitz, J. E. (2002). Information and the Change in the Paradigm in Economics. *American Economic Review*, *92*(3), 460-501.

Sweeney, L., & Coughlan, J. (2008). Do Different Industries Report Corporate Social Responsibility Differently? An Investigation through the Lens of Stakeholder Theory. *Journal of Marketing Communications*, *14*(2), 113-124.

Swift, C., Guide Jr, V. D. R., & Muthulingam, S. (2019). Does Supply Chain Visibility Affect Operating Performance? Evidence from Conflict Minerals Disclosures. *Journal of Operations Management*, *65*(5), 406-429.

Toppinen, A., & Korhonen-Kurki, K. (2013). Global Reporting Initiative and Social Impact in Managing Corporate Responsibility: A Case Study of Three Multinationals in the Forest Industry. *Business Ethics: A European Review*, *22*(2), 202-217.

Treacy, R., Humphreys, P., McIvor, R., & Lo, C. (2019). ISO14001 Certification and Operating Performance: A Practice-Based View. *International Journal of Production Economics*, *208*, 319-328.

United Nations Economic Commission for Europe. (2018). *Un Alliance Aims to Put Fashion on Path to Sustainability*. Retrieved 21 December from https://unece.org/forestry/press/un-alliance-aims-put-fashion-path-sustainability

Verbeeten, F. H., Gamerschlag, R., & Möller, K. (2016). Are CSR Disclosures Relevant for Investors? Empirical Evidence from Germany. *Management Decision*, *54*(6), 1359-1382.

Villena, V. H., & Dhanorkar, S. (2020). How Institutional Pressures and Managerial Incentives Elicit Carbon Transparency in Global Supply Chains. *Journal of Operations Management*, 66, 697-734.

Wang, Q., & Ngai, E. W. (2020). Event Study Methodology in Business Research: A Bibliometric Analysis. *Industrial Management & Data Systems*, 120(10), 1863-1900.

Wartick, S. L. (1992). The Relationship between Intense Media Exposure and Change in Corporate Reputation. *Business & Society*, *31*(1), 33-49.

Wei, X., Zhang, Z., Zhang, M., Chen, W., & Zeng, D. D. (2019). Combining Crowd and Machine Intelligence to Detect False News on Social Media. *MIS quarterly*, 46(2), 977-1008.

Wiengarten, F., Fan, D., Pagell, M., & Lo, C. K. Y. (2019). Deviations from Aspirational Target Levels and Environmental and Safety Performance: Implications for Operations Managers Acting Irresponsibly. *Journal of Operations Management*, *65*(6), 490-516.

Wiengarten, F., Lo, C. K., & Lam, J. Y. (2017). How Does Sustainability Leadership Affect Firm Performance? The Choices Associated with Appointing a Chief Officer of Corporate Social Responsibility. *Journal of Business Ethics*, *140*(3), 477-493.

Wiles, M. A., & Danielova, A. (2009). The Worth of Product Placement in Successful Films: An Event Study Analysis. *Journal of Marketing*, *73*(4), 44-63.

Wong, C. W., Lai, K.-h., Shang, K.-C., Lu, C.-S., & Leung, T. (2012). Green Operations and the Moderating Role of Environmental Management Capability of Suppliers on Manufacturing Firm Performance. *International Journal of Production Economics*, *140*(1), 283-294.

Wong, C. W., Wong, C. Y., Boon-Itt, S., & Tang, A. K. (2021). Strategies for Building Environmental Transparency and Accountability. *Sustainability*, *13*(16), 9116.

Xia, Y., Singhal, V. R., & Peter Zhang, G. (2016). Product Design Awards and the Market Value of the Firm. *Production and Operations Management*, *25*(6), 1038-1055.

Xia, Y., Singhal, V. R., & Zhang, G. P. (2016). Product Design Awards and the Market Value of the Firm. *Production and Operations Management*, *25*(6), 1038-1055.

Xu, M., Lai, I. K. W., & Tang, H. (2021). From Corporate Environmental Responsibility to Purchase Intention of Chinese Buyers: The Mediation Role of Relationship Quality. *Journal of Consumer Behaviour*, *20*(2), 309-323.

Xu, M., & Wong, C. W. Y. (2022). NLP-Based Event Recognition – Monitoring Sustainability Events Using Natural Language Processing and Machine Learning *Working Paper*.

Xu, M., Wong, C. W. Y., Wong, C. Y., & Boon-itt, S. (2022). Better to Talk More? The Impact of Sustainability Reporting on Productivity and Market Response from Signaling and Stakeholder Perspectives. *Working paper*.

Yang, Y., Orzes, G., Jia, F., & Chen, L. (2021). Does GRI Sustainability Reporting Pay Off? An Empirical Investigation of Publicly Listed Firms in China. *Business & Society*, *60*(7), 1738-1772.

Yang, Y., Zhang, K., & Kannan, P. (2022). Identifying Market Structure: A Deep Network Representation Learning of Social Engagement. *Journal of Marketing*, *86*(4), 37-56.

Yue, H., Zhang, L., & Zhong, Q. (2022). The Politics of Bank Opacity. *Journal of Accounting and Economics*, *73*(2-3), 101452.

Zhang, G. P., & Xia, Y. (2013). Does Quality Still Pay? A Reexamination of the Relationship between Effective Quality Management and Firm Performance. *Production and Operations Management*, *22*(1), 120-136.

Zhao, X., Li, Y., & Flynn, B. B. (2013). The Financial Impact of Product Recall Announcements in China. *International Journal of Production Economics*, *142*(1), 115-123.