Corporate Disclosure and Investor Sentiment: The Role of CSR Communication, Government Policies, and Audit Data Analytics

DISSERTATION

submitted in partial fulfillment of the requirement for the

degree of doctor rerum politicarum (Dr. rer. pol.) at

TU Dortmund University

Faculty of Business and Economics

Professorship of International Accounting and Auditing

by

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Dortmund

2023

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List of Abbreviations

a.a.O.	am angegebenen Ort
AG	Aktiengesellschaft
AICPA	American Institute of Certified Public Accountants
AKEIÜ	Arbeitskreis Externe und Interne Überwachung der Unternehmung
API	Application Programming Interface
AR	Abnormal Return
Art.	Artikel
Aufl.	Auflage
CAR	Cumulative Abnormal Return
COBE	Chicago Board Options Exchange
COVID-19	Coronavirus SARS-CoV-2
CSR	Corporate Social Responsibility
DAWG	Data Analytics Working Group
DJIA	Dow Jones Industrial Average
e.g.	exempli gratia
ECDC	European Centre for Disease Prevention and Control
ERP	Enterprise Resource System
ESG	Environmental, Social und Governance
et al.	et alii
EU	European Union
f.	folgende
FB	FaceBook
FE	Fixed Effects
Fn.	Fußnote
GeoRev	FactSet Geographic Revenue Exposure
GmbH	Gesellschaft mit beschränkter Haftung
GMT	Greenwich Mean Time
GNH	Gross National Happiness Index by FaceBook

H	Hypothesis
Hrsg.	Herausgeber
i.e.	id est
IAASB	International Auditing and Assurance Standards Board
ICS	Internal Control System
ID	Identification
IDW	Institut der Wirtschaftsprüfer
IDW PS	IDW-Prüfungsstandards
IESBA	International Ethics Standards Board for Accountants
IKS	Internees Kontrollsystem
Inc	Incorporation
ISA	International Standards on Auditing
ISA [DE]	German Adaption of the International Standards on Auditing
ISQC	Iinternational Standards on Quality Control
IT	Information Technology
ML	Machine Learning
MNC	Multinational Company
NLP	Natural Language Processing
NO.	Number
OLS	ordinary least squares
OxCGRT	Oxford COVID-19 Government Response Tracker
p.	page
PIE	Public Interest Entity
PO	Purchase Order
PPCA	Page Public Content Access
PTB	Price-to-Book Ratio
R	programming language
S&P	Standard & Poor’s
S.	Seite
SD	Standard Deviation

SEC	United States Securities and Exchange Commission
SIR	susceptible-infectious-recovered model
SVM	Support Vector Machine
T	Tausend
Tz.	Textziffer
u.a.	unter anderem
U.S.	United States of Americs
URL	Uniform Resource Locator
Vgl.	Vergleiche
VIX	CBOE Volatility Index
WEF	World Economic Forum
WHO	World Health Organization

Acknowledgements

This dissertation is the result of my work at the Professorship of International Accounting and Auditing at TU Dortmund University. I would like to thank a number of people who helped me accomplish this dissertation.

I want to express my deep gratitude to my doctoral supervisor Christiane Pott for giving me the opportunity to write this dissertation. Thank you for your guidance and support on all the projects I worked on and for giving me the freedom to conduct my own research and to express my uninhibited creativity at your chair. Throughout my time at TU Dortmund University, you have become a trusted contact, mentor, and counselor beyond professional matters.

I would also like to thank my co-author, Janine Maniora, for guiding my first steps through professional research and for the many steering in-depth talks we had.

Furthermore, I am thankful to all my colleagues who have accompanied and supported me throughout many joyful and memorable years at the chair, and to my parents and friends for their unconditional support.

1 Introduction

Investors rely on timely and accurate information when making decisions. Traditionally, information efficiency, as posited by the efficient market hypothesis, suggests that market prices fully reflect all available information, making it difficult for investors to consistently outperform the market (Malkiel 2003; Fama 1970). However, research has highlighted the presence of information asymmetry, in which market participants possess superior information that affects market performance (Barberis, Shleifer, and Vishny 1998). Disclosure practices and news play critical roles in the information dissemination process within capital markets. They have notable impacts on investor sentiment and influence asset prices, trading volumes, and market efficiency (Agrawal and Chadha 2020). This impact has been extensively studied in the field of behavioral finance. Empirical research suggests that investor sentiment can even deviate from fundamental valuations. Anxiety, uncertainty, overreactions, pessimism, risk avoidance and diminishing trust can cause price distortions and market inefficiencies (Tetlock 2007; Baker and Wurgler 2006; Barberis, Shleifer, and Vishny 1998).

With corporate financial disclosures, firms provide information that adheres to accounting standards and regulations, allowing investors to assess their financial health and performance. Over the last decade, firms are increasingly being encouraged to both mandatorily and voluntarily disclose non-financial information, such as Environmental, Social and Governance (ESG) disclosures, which seem relevant for investment decision-making (Hummel, Scholtens, and Sievänen 2020; Khan 2016). Moreover, dissemination channels change in the light of digital transformation. Social media platforms have fundamentally impacted corporate disclosure, enabling firms to disseminate financial and non-financial information, i.e., corporate performance or the commitment to Corporate Social Responsibility (CSR), online, timely and targeted (Blankespoor, Miller, and White 2014). They provide a two-way communication channel through which firms, investors, or other interest groups share their opinions. Hence, investors shift away from depending on information intermediaries such as analysts, advisors, and news agencies to gather valuable information. Instead, they increasingly turn to the collective opinion of the crowd or follow each other in herding behavior, mostly when there is little reliable information (Liu et al. 2018; Blankespoor et al. 2014; Tetlock 2007; Hirshleifer and Teoh 2003). These ways of direct and continuous communication can foster a sense of transparency and improve the relationship between firms and investors in times of the escalating societal role of non-financial corporate communication.

While firms may perfectly control the unidirectional flow and content of information in corporate disclosures, *news* plays a different role. Reaching a broader range of market participants, news often cover analysis, commentary, and interpretation of corporate disclosure, corporate performance, market events or governmental or institutional regulations (Tetlock 2010; Fang and Peress 2009). News may vary in terms of accuracy, objectivity, and the degree of analysis provided. News can lead to large-scale buying or selling of assets about specific companies, market sectors, or macroeconomic events, thus affecting market liquidity, trading volume, and the overall stability of the capital market (Bartov and Mohanram, 2007). Good news, such as strong positive economic indicators or CSR commitment, can stimulate investor confidence, leading to increased buying activity and a potential upward movement in security prices. Bad news, such as poor earnings reports or CSR scandals, can trigger investor fear, leading to selling pressure in the market. Research indicates that negative news can provoke more severe, enduring negative impacts on the stock market, in contrast to the positive effects of good news (Cohen et al. 2018; Jung et al. 2018; Miller and Skinner 2015).

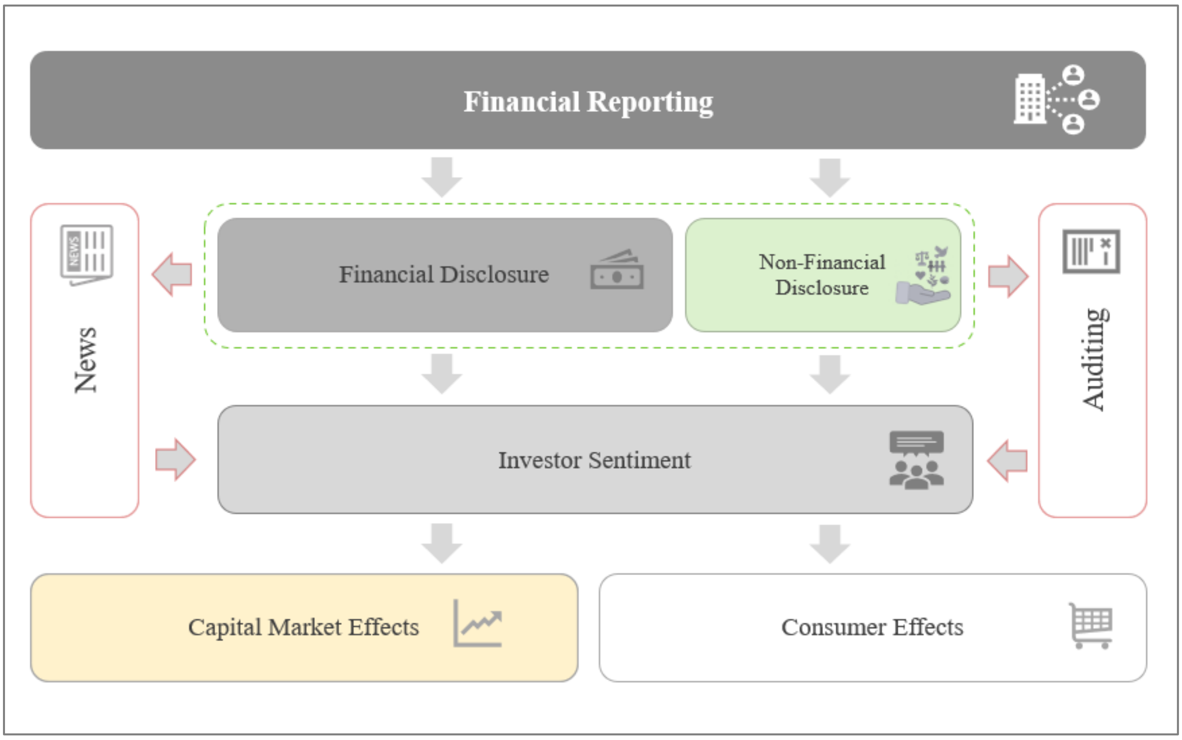
Exogenous shocks and crises amplify the impact of investor sentiment on capital markets. For instance, the rapid spread of the COVID-19 pandemic and subsequent lockdown measures created high levels of uncertainty about the duration and severity of the crisis, as well as its economic and environmental impact. Investors became uncertain about the prospects of companies, industries, and the overall economy, leading to heightened anxiety and fear in capital markets (Naseem et al. 2021; Baker et al. 2020). Governments worldwide have implemented measures to mitigate the impact of the pandemic. Containment and closure strategies, health initiatives, and economic support packages to support financial markets and stabilize the economy were among the actions taken. Some investors appreciated the measures, as governments indicated a commitment to mitigate the negative economic impact of the pandemic. Others remained pessimistic and contributed to the market drop by trading conservatively or irrationally. As such, news regarding regulators' decisions throughout a global crisis, both serving and restrictive, has considerable impact on the capital market. In addition, firm characteristics, such as financial resilience, have a steering effect on investors' reactions (Beer, Maniora and Pott 2023).

In this firm-investor relationship, auditing assumes a unique function, acting as a moderator in the interaction between market participants. To maintain market stability, auditing may reduce information asymmetry to minimize the likelihood of market fluctuations driven by misinformation or a lack of information (Varici 2013). The presence of reliable and independent audits strengthens investors' trust in the information's precision and dependability, may attract a greater number of investors, and motivates well-informed investment decisions (Aobdia 2015). Moreover, audits verify that companies' disclosures, both mandatory and voluntary, comply with accounting standards and regulations, ensuring that corporate information is accurately and transparently presented (Christensen et al. 2020). Auditing results can provide an additional layer of confidence for investors when evaluating information presented in the news. Positive audit outcomes may enhance the credibility of good news and help investors assess potential risks associated with negative news. As emphasis on corporate responsibility and sustainability grows, auditing has expanded beyond financial disclosures to include non-financial reports. This shift signifies a broader recognition of *double materiality*, the two-way interaction between corporations and their environment, underscoring the need for transparency in these areas in addition to financial integrity (Baumüller and Sopp 2022). However, non-financial auditing is complex and resource intensive. Several standards and frameworks are available for ESG reports. Moreover, the collection of accurate and reliable ESG data is challenging. It requires systems to capture ESG data accurately, which can often be qualitative and subjective, making verification difficult. Thus, efficient auditing has become increasingly important. *Audit efficiency* has been studied in a broad strand of literature. Referring to the way audit tasks are carried out, audit efficiency generally describes a minimization of the resources used without sacrificing the quality of the audit (Knechel et al. 2012). This includes the effective planning, execution, and reporting of the audit process. Increasing efficiency can lower audit costs, reduce the time taken, and improve reporting timeliness. On the one hand, aiming for audit efficiency could compromise audit quality if it accelerates the audit process or devalues materiality, leading to a higher risk of failure in uncovering inaccuracies and fraudulent activities (Knechel et al. 2012). On the other hand, focusing on audit quality without regard to efficiency could result in unnecessarily protracted audits and excessive costs (Kinney et al. 2004). Modern audit techniques, including the use of technology, i.e., Process Mining, can help achieve a balance. They may automate routine audit tasks, enhance risk assessment, and improve fraud detection through a more efficient allocation of auditors' time

(Appelbaum et al. 2017). The integration of process mining into the auditing process has the potential to enhance the efficiency and quality of audit procedures. (Pell, Beer and Pott 2023).

This dissertation consists of three essays, which were written independently of each other and are diverse in their topics; yet, they all share a common ground and aim to contribute to a better understanding of the relationship between financial reporting, news, auditing, investor sentiment, and the capital market. All three essays either apply data analytics to provide arguable in-depth insights or discuss the implications of the integration of data analytics in practice. Figure 1 provides an overview of the interconnection between financial reporting, news, auditing, investor sentiment, and the capital market.

Figure 1: Interconnection of Financial Reporting, News, Auditing, Investor Sentiment, and the Capital Market



The *first paper* of this dissertation ("The Risk of Silence - How the Capital Market Penalizes Social Media Passivity") investigates the moderation effect of passive corporate social media communication in the relationship between investor sentiment and firm-level stock returns. New technology has caused a shift in the communication channels used for both financial and non-financial corporate disclosures, leading to a significant change in the information environment (Cade 2018). As investors increasingly rely on social media for financial and corporate news (Liu et al. 2018; Blankespoor et al. 2014; Gartner 2010; Tetlock 2007), we hypothesize that firms that fail to participate in this conversation are likely to be noticed for their silence by their investors, most likely when they operate in a homogenous information environment, i.e., the Dow Jones Industrial Average. We build on the wisdom of crowds (Hong and Page 2004; Surowiecki 2004) and the herding theory (Hirshleifer and Teoh 2003) to explain the formation of social media user sentiment. The theory describes a phenomenon in which the aggregation of information provided by a diverse group of intelligent decision makers (i.e., non-experts) leads to better decisions than the information of individual experts or less diverse groups with superior skills. The herding theory posits that individual market participants are most likely to follow the aggregated opinion of the crowd when they are uncertain about the validity of a given information set. Cade (2018) finds that firms can positively influence investors' perceptions by actively addressing criticism on Twitter. When a firm receives public criticism on social media, investors respond more favorably when the firm provides an active explanation compared to not responding at all. This effect may be attributed to the theory of cognitive dissonance, which suggests that individuals strive for consistency within their beliefs and attitudes towards firms (Kahneman and Tversky 1979; Festinger 1957). Investors experience mental discomfort when there is a contradiction between their beliefs and the available information about a firm's stock performance. By timely intervening and reactivating posting activity on the firm's corporate Facebook page after a period of passivity, this negative relationship between user sentiment toward the firm and its future stock prices may be mitigated over time. We employ a large-scale machine learning approach to measure a firm's daily social media sentiment in a broad sample of user comments (3,502,532) on its corporate Facebook page over an eight-year period from 2009 to 2016. Specifically, we build a Support Vector Machine (SVM) for the classification of Facebook comments into positive, negative, and neutral sentiment (Antweiler and Frank 2004; Madge and Bhatt 2015; Pang, Lee, and Vaithyanathan 2002). To measure posting passivity, we use two approaches: comparing the daily number of posts of each firm to the firm's peers, and considering the firm's historical posting activity as a reference. We find that if a firm remains passive on Facebook for a period starting from five days, it may counteract the positive influence on stock returns generated by prior positive sentiment. When subjected to negative sentiment, a week of passive communication on Facebook intensifies the negative sentiment's impact on future stock returns. Additionally, we reveal that the more prolonged the company's Facebook passivity, the longer it takes for the company to mitigate the adverse effects of such passivity. The length of time required for this mitigation depends on when the company resumes posting after a period of inactivity. These findings apply to both ways of measuring a firm´s passivity, whether relative to its competitors or past social media behavior. As such, it appears that Facebook users begin to penalize a company's Facebook inactivity after just a few days, even if they initially express positive sentiment towards the company. Our work provides insights for firms that actively use or consider using social media as a communication channel for both financial and non-financial disclosures. Firms that are aware of the consequences of abandoning their social media platforms might be able to anticipate and strategically manage their reputations among investors. Our study is also relevant to regulators assessing the risks and benefits of using social media as a corporate disclosure platform. This study adds to the research on the impact of new communication channels on corporate disclosures and their impact on firm investors, highlighting the importance of continuity when using social media as a dissemination channel for corporate information.

While the first paper adds to the literature on the impact of corporate disclosures on investor sentiment (e.g., He et al. 2020; Chau et al. 2016; Beer and Zouaoui 2012; Cormier et al. 2010; Fang and Peress 2009; Kaniel et al. 2008; Hong and Stein 2007; Baker and Wurgler 2006), little is known about the mechanisms that form investor sentiment during pandemic crises. Funck and Gutierrez (2018) investigate how Ebola-related news headlines affected the stocks that received media attention. The findings indicate that stock prices usually undergo a reversal within the day following a news release. Recently, Engelhardt et al. (2020) discover that stock market downturns in 64 nations due to COVID-19 are more linked to heightened media coverage than to rational expectations. As governments worldwide took action to mitigate the social and economic consequences of the pandemic, the role of government responses in shaping investor sentiment has become a focal point of interest in behavioral finance research (Alexakis et al. 2021; Hale et al. 2020; Salisu and Vo 2020). However, research is at the very beginning. The influential role of different types of government responses, i.e., serving or restricting, is yet to be explored. Moreover, it is an open question whether firms' characteristics may moderate this impact. For instance, there is a lack of knowledge on the link between a company's sales side, specifically sales revenues, and investors' assessments of the COVID-19 situation in countries where a significant portion of the company's revenue is generated. Thus, the *second paper* ("COVID-19 Pandemic and Capital Markets: The Role of Government Responses") examines the moderating effect of government responses on the impact of the COVID-19 pandemic, proxied by the daily growth in COVID-19 cases and deaths, on the capital market, that is, the S&P 500 firm´s daily returns. The global stock market experienced a tumultuous period during the COVID-19 pandemic, with the S&P 500 index dropping by over 30% from its peak in January, 2020. This decline most likely refers to unprecedented uncertainty among investors (Baker et al. 2020; Zhang et al. 2020). However, the index rebounded swiftly, recovering to its pre-pandemic value within 26 days of the WHO's pandemic declaration in March 2020, and surpassing its January peak by August 2020. This rapid recovery raises questions regarding the drivers of investor sentiment during health crises. We hypothesize that different types of government responses announced to the COVID-19 pandemic shape investor sentiment, resulting in varied effects on the relationship between COVID-19 case growth rates, death tolls, and stock market responses. Restrictive measures may dampen investor confidence, amplify pessimism, and lead to market overreactions. Likewise, investors may also value proactive government interventions, recalibrate their market outlooks, and subsequently make more optimistic investment choices. Thus, governments have the potential to diminish ambiguity, gain investor confidence, and indirectly influence the stock market dynamics. We anticipate that this dual impact will play a vital role in the swift rebound of stock markets during the pandemic. We employ the Oxford COVID-19 Government Response Tracker (OxCGRT) to monitor 16 daily indicators of government actions across 180 countries from January 1, 2020, to March 15, 2021. These indicators span three countermeasures: containment and closure strategies, economic support, and health system support policies (Hale et al. 2020). Daily data on worldwide confirmed COVID-19 cases and deaths per country, from January 1, 2020, to March 15, 2021, was sourced from the European Centre for Disease Prevention and Control (ECDC). In a unique dataset, we gather the revenues specific to each S&P 500 firm realized in each country. This setting allows us to attribute government responses from countries relevant to each firm. In a subsequent model, we examine whether investors exhibit distinct awareness and reactions based on a company's direct revenue exposure to COVID-19. Results show that aggregated government responses mitigate the decline of stock returns due to rising COVID-19 cases and deaths. Government actions in the field of containment and closure, as well as economic support, were particularly appreciated by investors, mitigating the negative stock market impacts induced by the pandemic. Conversely, government initiatives related to health systems were associated with further declines in abnormal stock returns, possibly due to the delayed nature of these responses in the initial stages of the pandemic. For firms with high revenue exposure to COVID-19, the mitigation effect was more pronounced for government economic support and health system initiatives. However, the containment and closure policies did not yield significant results in this context. Our study contributes to the literature on investor sentiment during crisis situations precipitated by external shocks. This highlights the role of government announcements in moderating the impact of crises on capital markets. Moreover, the findings emphasize the importance of considering firm-specific characteristics, i.e., financial resilience, in understanding investor reactions during crises situations. In line with prior literature on the firm-investor relationship, our results provide critical insights for firms in strategizing investor relations. Companies are interested in formulating communication strategies in response to pandemic crises based on government policies. Additionally, investors in multinational corporations (MNCs) may incorporate the policies of various governments when making trading choices.

Paper one and two provide insights into the interplay between firms and investors in dynamic information environments. However, this relationship is most likely moderated by external auditing, with audit efficiency playing a pivotal role in balancing audit costs and quality. Hence, the *third paper* ("Der Abschlussprüfer als Data Scientist? Über die Chancen und Herausforderungen des Einsatzes von Process Mining in der Wirtschaftsprüfung") sheds light on how data-analytic technologies, specifically Process Mining, impact audit efficiency.

Following digital transformation, firms integrate information technology (IT) solutions aimed at harmonizing systems, processes, and data. This integration leads to an increase in the volume and complexity of the data processed and stored within firms. In addition, new reporting obligations on non-financial topics such as ESG reports have expanded the scope of audits. Therefore, cost pressures increase for firms under audit, while high standards of audit quality and security may be maintained. The high volume and diffuse structure of the data must undergo a transformation process to become a viable source of information for the audit process (Ziegler et al. 2018). It allows access to historical data to facilitate the visualization and analysis of actual business processes as they occur within the firm, uncovering inaccuracies in process flows, and facilitating the targeted expansion of individual case examination actions (Marten 2020). However, the specific application of Process Mining to auditing remains unspecified. Thus far, the literature leaves open questions about the implementation, prerequisites, normative foundations, necessary resources, and documentation procedures for the integration of Process Mining in the audit process. These uncertainties, coupled with a lack of "best practices", may contribute to auditors' preference for conventional auditing methods. Particularly, practice calls for regulations in the use of Process Mining for auditors, focusing on whether there is a need for auditors to deepen their knowledge in data management despite having interdisciplinary professional qualifications. Thus, we argue that Process Mining may serve as an assistive component in auditing, aiding in delineating a clearer picture of business processes, their characteristics, and weaknesses.

Process Mining decomposes actual business processes, enabling the visualization of individual steps and different process variations. The traditional risk-oriented audit approach is complemented, as the process structure determination relies on data analytic methods rather than solely on personal observations, documentation reviews, employee interviews, or prior knowledge about the process, which requires substantial time and resources (Ruhnke and Martens 2020). Process Mining tools can capture events related to a process in the correct sequence, that is, an Event Log. This allows the structuring of unstructured, incomplete, and non-chronologically recorded transactions into logical process chains that were previously invisible. The quality of Event Logs improves with the amount of data stored in the event. Process Mining can then be conducted in three ways: *discovery*, where a process model is created solely based on extracted Event Logs; *Conformance Checking*, where Event Logs are compared with a known process model of the company to identify and diagnose deviations from the expected process; and *enhancement*, where insights from the Event Log are used to revise and supplement the existing process model, not considering it as the expected state (van der Aalst et al. 2012).

Challenges arise for both the firms and auditors. Firms must demonstrate a high level of IT maturity, and data must be fully and consistently obtainable. The demand for data security in auditing is escalating and necessitating corporate cooperation. Regarding IT security and data protection, the transfer of data between firms and auditors can be exposed to data theft, manipulation, and fraud. In addition to establishing security barriers, auditing firms face the challenge of sensitizing auditors to appropriately respond to both planned and acute issues pertaining to data protection and IT security.

To better understand these challenges, we explore a conceptual approach of how Process Mining can be integrated into Internal Control System (ICS) auditing, using a simplified, fictional example of a procurement process. We provide a fictional firm structure with a high degree of digitalization and processing of order transactions through an efficient and compatible ERP system, with all procurement activities occurring internally. We create a predefined target process model, “Purchase Order,” and identify and visualize the actual process models. This approach allows the comparison of intended and real processes, enabling the identification of deviations and potential risk points. In our example, 41.62% of Purchase Orders conform to the target model, whereas the remaining 58.38% represent variants with unique characteristics and potential risks. Some structures miss crucial activities, while others exhibit financial risks due to the sequence of activities, such as paying invoices before receiving goods.

Overall, our example shows, that Process Mining supported auditing can illuminate individual transactions, identify outliers, and offer dynamic visualizations of process structures. It may provide auditors with insights into the relationships between company transactions. However, it may only serve as a supportive tool in the auditing process. The procedural discrepancies identified still require thorough examination, evaluation, and justification within the audit risk model. Interpreting processed firm data requires a high level of industry and company knowledge.

This dissertation is a cumulative work consisting of three individual papers related to financial and non-financial corporate disclosures. Please note that some papers have already been published, are under review, or will soon be in the review process for publication. Therefore, it is likely that further adaptations of the individual paper versions presented in this dissertation will take place afterwards. Subsequent versions of the papers will be available in the respective journals or scientific platforms after publication. Thus, please ensure that only the latest versions of the paper are cited.

2 The Risk of Silence - How the Capital Market Penalizes Social Media Passivity

2.1 Publication Details

Authors: Christian Beer, Janine Maniora and Christiane Pott

Abstract: This paper examines the capital market effects on a firm's temporary social media passivity relative to (a) its peers and (b) its historical social media activity. Specifically, we examine to what extent passivity on the firm's corporate Facebook page influences the relationship between the sentiment among social media users toward the firm and its future stock prices. We find that a longer period of posting passivity by the firm, starting from a five-day period, is likely to reverse even a positive effect of positive sentiment on the firm's future stock prices. In other words, Facebook users seem to penalize the firm's social media passivity after a few days. In the event of negative sentiment, we find that one week of social media passivity results in amplified negative sentiment on the firm's future stock prices. Moreover, we find that the longer the firm is passive, the longer it takes to overcome the negative effects of the posting passivity by resuming posting.

Keywords: Behavioral Economics; Investor Sentiment; Wisdom of Crowds, Machine Learning; Social Media; Stock Returns

JEL-Codes: D91, G40, M15, M40, M41

Publication Status: Published. Journal of Information Systems 2024, 1-34. https://doi.org/10.2308/ISYS-2023-059. Previous versions of this paper were presented at the 43th European Accounting Association (EAA) Annual Conference, August 2020, the European Accounting Review (EAR) Annual Conference, November 2020, the 105th Annual Meeting of the American Accounting Association (AAA), August 2021, and the 45th European Accounting Association (EAA) Annual Conference, May 2023.

2.2 Introduction

If you post too infrequently, your audience will forget that you exist, and you will quickly fade into the deep dark recesses of their minds. However, if you are posting too often, you will become a complete nuisance and they will dread seeing your posts overcrowding their feed.
(Neil Patel 2016)

This paper analyzes whether and how the capital market reacts to a firm's temporary social media passivity relative to (a) its peers and (b) its historical social media activity. Social media is increasingly used by firms to disclose corporate information, such as earnings releases or other sensitive, market moving news (Blankespoor, Miller, and White 2014). This significantly changes the dissemination of information and requires a new way of assessing investor sentiment and its effect on the capital market. Prior research indicates that sentiment expressed by users on social media can affect stock market returns and that firms are able to reduce information asymmetry in a timelier fashion (e.g., Bartov, Faurel, and Mohanram 2018; Blankespoor 2018; Cade 2018; Twedt 2016; Blankespoor et al. 2014; Zhou, Lei, Wang, Fan, and Wang 2014; Bollen et al. 2011b). In a recent study, He, Hong, and Wu (2020, p. 551) find that 'the relation between accounting variables and stock returns varies with investor sentiment', and that 'the evidence is consistent with mood affecting investors' use of information processing strategies'. However, these studies do not consider that positive, negative, and neutral user sentiment is likely to have a different effect on the capital market in terms of strength, duration, and turnaround time, nor the moderating effects of a firm's posting activity during different states of sentiment. Specifically, we examine to what extent passivity on a firm's corporate Facebook (FB) page influences the relationship between positive, negative, and neutral sentiment among social media users toward the firm and its future stock prices.

Jung, Naughton, Tahoun, and Wang (2018) find that firms seem to strategically disseminate financial information on social media platforms with a tendency to disseminate less likely when the news is bad or when the magnitude of the bad news is worse. Thus, a firm can choose to pause social media activity or to increase its social media activity for various reasons. Cade (2018) shows that investors—as consumers of 'corporate disclosure'—incorporate their knowledge of a firm's motives, information sharing strategies and persuasion tactics, as well as other investors' motives into their process of evaluating a firm, when processing a firm's social media posting. Thus, the passivity of a firm on its social media platforms may increase cognitive dissonance among investors since information available to the market cannot appropriately be verified or refuted by a firm. The absence of corporate information might even strengthen investors' doubts about having made the right investment decisions. Thus, individual market participants are most likely to herd (Hirshleifer and Teoh 2003) and to follow the aggregated opinion of the crowd (e.g., Liu, Meng, You, and Zhao 2018; Blankespoor et al. 2014; Gartner 2010; Tetlock 2007), when they are uncertain about the validity of a given information set. Besides the wisdom of crowds and herding theory, we use the theory of cognitive dissonance to examine the effect of social media passivity on user sentiment and investors' trading decisions.

We focus on a homogenous group of firms, i.e., the 30 largest U.S. firms listed in the Dow Jones Industrial Average (DJIA) index, for the period 2009–2016. We are particularly interested in this group of firms because of their overall high social media activity and homogenous performance. Jung et al. (2018) find that by the end of 2013 52 percent of the S&P 1500 firms already adopted a social media platform for corporate disclosures and that 57 percent of firms were to primarily use social media for disclosing financial information—with a significant correlation to firm size. We define a firm's social media activity as being low when (a) its posting activity on FB is below average compared to its peers or (b) its posting activity on FB is below average compared to its historical social media activity. We employ a large-scale machine learning (ML) approach using a support vector machine (SVM) to measure a firm's daily sentiment on FB. We define social media sentiment as the FB community's mood transferred by user comments to a firm's FB post. The following user comments are examples of the type of data used in our sample to build the aggregated daily user sentiment on FB toward a firm:

> *Coca-Cola's ads are the most phenomenal I ever know…There is always something that relates to me… directly. Love them! #alwayswatching (User comment on an FB post by Coca-Cola)*
>
> *Spent more than 13 years of my life at IBM and are still very proud to be an #IBMer (User comment on an FB post by IBM)*
>
> *I had horrible experience with your customer service (User comment on an FB post by American Express)*

Stop polluting the environment (User comment on an FB post by ExxonMobil)

Now I know you change the logo (User comment on an FB post by Microsoft)

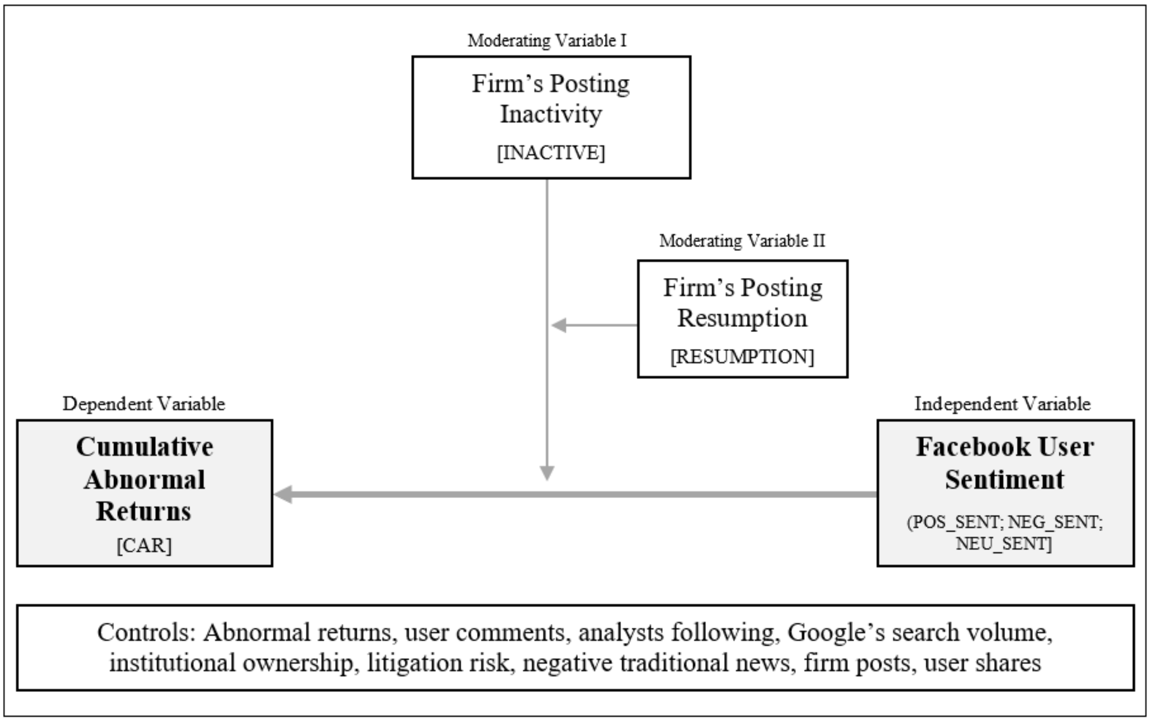
While the first two comments are classified as positive sentiment, the third and fourth comments fall into the negative sentiment category. The last comment constitutes neutral sentiment. We separately analyze positive, negative, and neutral sentiment to shed light on the different effects of firms' posting behavior in every sentiment state.[1] More classification examples are provided in Appendix 1.1.

In total, our final sample consists of 2,940,252 FB comments. We manually classify 34,531 FB comments for the creation of the training and test sets to train the supervised ML algorithm. On average, our sample firms receive 21 percent positive, 7 percent negative, and 72 percent neutral comments per observation day.[2] We use different time windows for measuring social media sentiment and the firm's posting passivity on FB, i.e., one, three, five and seven day(s) prior to the measurement date of a firm's (adjusted) cumulative abnormal returns over a three-day window. This allows us to examine the consequences of user sentiment on FB on the capital market dependent on the length of the firm's posting pause (i.e., posting passivity), as well as the continuing effects of a pause when the firm has restarted its posting activity (i.e., posting reactivation). Figure 2.1 illustrates our research design.

[1] Rather than creating a sentiment index that is scaled from minus one to one, whereby negative values indicate more negative sentiment and positive values more positive sentiment (e.g., Mao et al., 2011; Li, 2010; Das & Chen, 2007), we classify each comment into either the positive, negative, or neutral category.

[2] Prior literature finds that people express themselves positively rather than negatively on Facebook, as negative emotions are not socially favorable and people tend to suppress negative emotions in public (e.g., Gross et al., 2006). As such, the distribution of positive, negative, and neutral comments is common for social media platforms and is in line with prior literature.

Figure 2.1: Research Design.

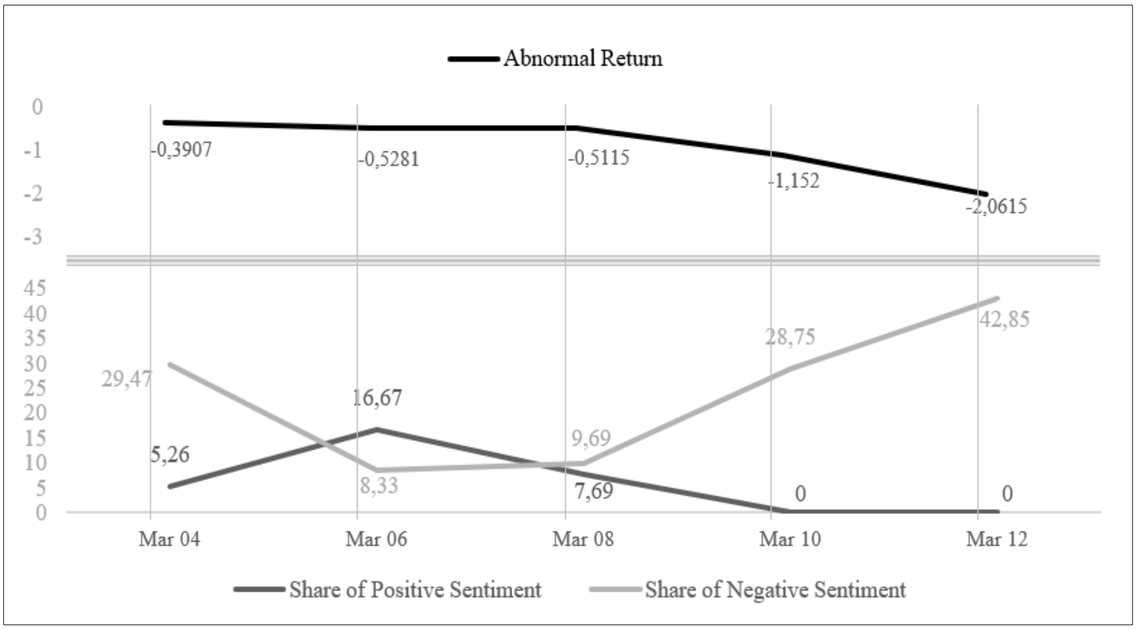


Notes: This figure represents the design of our main regression model: Facebook User Sentiment, derived from the gathered FB comments and classified in an ML approach, serves as the independent variable. Cumulative Abnormal Returns, measured as adjusted abnormal returns cumulated over each three-day period around the observed day, is the dependent variable. We employ two moderator variables to test for interactions with our sentiment measures: Firm's Posting Passivity indicates posting passivity on a firm's corporate FB page relative to its peers or its historical social media activity and Firm's Posting Reactivation indicates new posting activity following a period of passivity of different length. Furthermore, we control for a set of variables that are traditionally assumed to influence the capital market, e.g., analyst following or institutional ownership, as well as variables that particularly influence investor sentiment, e.g., the strength of negative news in traditional media outlets, Google's search volume, or litigation risk.

Our results indicate that a longer period of posting passivity on FB by the firm, starting from a five-day period, is likely to reverse even a positive effect of positive sentiment on the firm's future stock prices. When exposed to negative sentiment, we find that one week of passivity on FB amplifies the impact of negative sentiment on the firm's future stock prices. Moreover, we find that the longer the firm is passive on FB, the longer the firm takes to neutralize the negative effects of posting passivity. This neutralization time depends on the firm's posting reactivation after a period of posting passivity. These results hold true for both methods of measuring a firm's passivity, either in comparison to its peers or in comparison to its historical social media activity. In conclusion, FB users seem to penalize the firm's FB passivity after a few days even when FB users have initially expressed positive sentiment toward the firm.

Figure 2.2 shows an exemplary course of Walmart's FB user sentiment and its daily abnormal stock returns dependent on its posting passivity. Specifically, it illustrates the relationship between daily social media sentiment and daily abnormal stock returns during a posting passivity period as compared to its peers in our DJIA sample from March 4, 2015 to March 12, 2015. The figure shows a significant increase of negative sentiment and a corresponding decrease of positive sentiment starting from March 8, 2015 through March 9, 2015 until March 12, 2015. After four to five days of posting passivity on FB, Walmart's negative sentiment manifests among FB users and has a negative effect on the firm's daily abnormal returns. The daily abnormal return decreases significantly starting from March 8, 2015. On March 12, 2015 the negative abnormal returns have almost quadrupled on a daily basis.

Figure 2.2: Example: Walmart.



Notes: This figure shows the relationship between daily social media sentiment and daily abnormal stock returns for Walmart during a total posting passivity period relative to the firm's peers (PASSIVEpeer), i.e., the number of the firm's postings on its FB business page is zero, from March 4, 2015 to March 12, 2015. The upper section provides the daily percentage of abnormal stock returns. The lower section provides the daily percentage shares of both positive and negative FB comments. Values for neutral sentiment are omitted for visibility.

We contribute to practice (e.g., firms and regulators) and research in several ways. First, our results are practically relevant to firms that are active on social media platforms or consider getting actively involved in the near future, even for those operating in already rich information environments worldwide. Firms that are aware of the consequences of neglecting their social media communication might be able to better anticipate investor reactions and strategically manage their reputation amongst investors. Moreover, our results are relevant to regulators debating the costs and benefits of firms' use of social media for international capital market communications. While the SEC approved the use of social media platforms as an official disclosure venue as early as April 2013, other regulators around the world lag behind. However, even unregulated social media platforms can influence stock markets, although the information from postings may be uninformative or even intentionally misleading (e.g., Bartov et al. 2018). Our paper therefore adds to the current discussions about social media regulation around the world.[3]

Second, our study extends the research on the effects of corporate social media use on the stock market (e.g., Bartov et al. 2018; Blankespoor 2018; Cade 2018; Hales, Moon, and Swenson 2018; Jung et al. 2018; Elliott, Loftus, and Winn 2017; Lee, Hutton, and Shu 2015; Miller and Skinner 2015; Blankespoor et al. 2014; Chen, De, Hu, and Hwang 2014; Curtis, Richardson, and Schmardebeck 2014; Sprenger, Tumasjan, Sandner, and Welpe 2014), since our paper is the first to shed light on the capital market consequences of a firm's social media passivity. Furthermore, our study contributes to the literature on investor sentiment and its effects on a firm's stock returns (e.g., He et al. 2020; Chau et al. 2016; Beer and Zouaoui 2012; Cormier et al. 2010; Fang and Peress 2009; Kaniel et al. 2008; Hong and Stein 2007; Baker and Wurgler 2006; Hong and Stein 1999; Shleifer and Vishny 1997; Palomino 1996; Long, Shleifer, Summers, and Waldmann 1990). Prior studies measure investor sentiment by using stock market statistics, i.e., the number of executed orders as a proxy for an investor's mood state (Kaniel, Saar, and Titman 2008), trading volume, dividend premiums, the number of public offerings and equity shares (Baker and Wurgler 2006), or based on survey designs (e.g., He et al. 2020; Chau, Deesomsak, and Koutmos 2016; Beer and Zouaoui 2012; Baker and Wurgler 2006). While past studies link investor sentiment mainly to news flows in traditional media (e.g., Hong and Stein 2007; Hong and Stein 1999; Fama

[3] For example, the European Commission is currently considering a Code of practice against disinformation on social media platforms (since 2019) and Germany is debating a network enforcement law, also called 'the FB law' (since 2017).

1995; Malkiel and Fama 1970), we extend this view with regard to social media communication. This development is imperative since social media platforms promote public and uncensored two-way communication between individuals and firms and, thus, play an important role in influencing stock markets by shaping investors' opinion (Cade 2018). Moreover, facilitating information dissemination through social media platforms increases the influencing power of noise trading (Baker and Wurgler 2006),[4] which implies the need of a broader investor sentiment definition. We address these issues by using social media 'user' sentiment as a proxy for 'investor' sentiment and shed light on the relation between social media user sentiment and its power to indirectly influence capital market developments dependent on the firm's posting activity.

The remainder of the paper is organized as follows. In section 2, we review the related literature and present our research questions. We describe our data and research design in section 3. In section 4, we present our findings, while we clarify additional analyses and robustness tests in section 5. Finally, we discuss our findings in section 6 and conclude.

2.3 Background and Hypothesis

2.3.1 How can Social Media affect the Capital Market?

Instead of relying on information intermediaries, such as analysts, advisors, or news agencies, to gather value-relevant information, individual stock traders increasingly follow the aggregated opinion of the crowd (e.g., Liu et al. 2018; Blankespoor et al. 2014; Gartner 2010; Tetlock 2007). The wisdom of crowds describes a phenomenon where the aggregation of information provided by a diverse group of intelligent decision-makers, i.e., non-experts, leads to better decisions than the information of individual experts or less diverse groups with superior skills (Hong and Page 2004; Surowiecki 2004). In other words, the aggregated set of solutions from a group of individuals performs better than the majority of individual solutions (Yi, Steyvers, Lee, and Dry 2011). For example, Azar and Lo (2016) find that the aggregate return forecasts shortly before and after meetings of the Federal Open Market Committee outperform most individual forecasts. According to Moldoveanu and Martin (2010), the diversity of a group beats the individual skills of each group member. Since a

[4] According to Palomino (1996), investors trade either rationally or based on noise. While rational traders have Bayesian beliefs and do not act impulsively, noise traders act randomly based on noisy signals (Shleifer and Vishny, 1997).

group of social media users is highly diverse, the wisdom of crowds may explain a potentially predictive power of social media sentiment for future stock returns.

Another phenomenon that might be influencing the effects of social media sentiment on stock markets is ‘herding’. Herding describes the behavior of market participants following each other from security to security and from market to market (Choi and Skiba 2015). For example, Hirshleifer and Teoh (2003) find that individual market participants are most likely to herd when valid information is rare and unjustifiable. They argue that the ‘herding instinct’ seems to be stronger in stressful situations, particularly when prior expectations of the market development were not met. Welch (2000) shows that market analysts tend to herd, and herding behavior occurs mostly when there is little reliable information. Hong, Kubik, and Solomon (2000) stated that herding is exhibited often by less experienced analysts and that these analysts are less likely to issue timely forecasts. They also tend to reverse their forecasts more frequently. Since most stock market participants who use social media as a basis for trading decisions are non-expert traders, herding might be a considerable phenomenon when analyzing the effects of social media sentiment on the stock market.

2.3.2 Corporate Social Media Passivity

The theory of cognitive dissonance (Festinger 1957) has been employed in numerous economic studies to explain the association of investor sentiment and trading decisions. In general, it describes a situation of psychological distress that occurs with contradictory beliefs, ideas, assumptions, or attitudes (Kahneman and Tversky 1979). Most commonly, in a stock market setting, this contradiction is explained with the mental conflict that optimistic investors experience when becoming aware of negative news about the firm they invested in. Investors tend to relieve this discomfort by acting irrationally, e.g., selling shares (Antoniou, Doukas, and Subrahmanyam. 2013).

Cade (2018) shows that investors—as consumers of ‘corporate disclosure’—incorporate their knowledge of a firm’s motives, information sharing strategies and persuasion tactics, as well as other investors’ motives into their process of evaluating a firm. Ferris (1989, p. 178) even describes investors as ‘customers for the firm’s most important product, namely, the firm itself’. In consumer research, successful social media management strategies evidently have a powerful impact on a firm’s performance, e.g., increased revenue, reduced customer acquisition costs and greater profitability (Lam, Shankar, Erramilli, and Murthy 2004). However, they require not only social media analytics for monitoring the public data stream but more importantly active participation through interaction (Risius and Beck 2015). This means—in a social media disclosure setting—investors expect firms to proactively engage, react to certain events, and interact with their user community.

As a consequence, the passivity of a firm on its social media platforms may increase cognitive dissonance among investors, since the information available to the market cannot be verified or refuted by a firm and users' attention cannot be redirected to positive news in a timely fashion. Moreover, the absence of corporate information might strengthen investors' doubts about having made correct investment decisions. One way to mitigate investor uncertainty is to increase social media postings–especially for firms with bad news (Miller and Skinner 2015). In a study examining product recalls, Lee et al. (2015) find that firms that are more proactive in using social media to manage the crisis experience a weaker negative market reaction.

In line with the theory of cognitive dissonance, triggering investors' negative expression due to firms' social media passivity, we expect that investors are more likely to herd (Hirshleifer and Teoh 2003) and to follow the aggregated opinion of the crowd (e.g., Liu et al. 2018; Blankespoor et al. 2014; Gartner 2010; Tetlock 2007), which causes sentiment on social media to rapidly disseminate in times of posting passivity. Therefore, we hypothesize as follows:

> **H_1**: *A firm's temporary posting passivity on FB negatively affects the relation between user sentiment toward the firm and its future stock prices.*

2.3.3 Reactivation after Social Media Passivity

In an experimental study, Cade (2018) finds that by actively addressing criticism on Twitter, firms are able to manage investors' perceptions. In the case of a firm being criticized publicly on social media, investors favor an active explanation by the firm over no response. Combined with the theory of cognitive dissonance, it seems that investors' mental discomfort due to the absence of firm-side information in a situation of contradiction between their beliefs and information regarding the development of a firm's stock may be mitigated by a timely intervention. We therefore expect that a reactivation of posting activity on a firm's corporate FB page—after a period of posting passivity—mitigates the negative relationship between user sentiment toward the firm and its future stock prices over time:

> ***H₂***: *After a period of posting passivity, a firm's reactivation of postings on FB mitigates the negative relationship between user sentiment toward the firm and its future stock prices over time (three-way interaction).*

2.4 Data and research design

2.4.1 Facebook Data

We identify the official FB accounts, i.e., FB business pages, of the 30 largest U.S. firms listed in the DJIA index for the period 2009–2016. We collect all comments that a posting by the firm received within our sample period by using FB's Application Programming Interface (API).[5] In total, we collect 3,502,532 comments (14.241 daily average) from FB for our sample firms in our sample period. Instead of relying on third party applications, we program the API link manually to make sure the information retrieval is reliable and complete. Further, we only include firms that host a corporate FB page for at least one year within our sample period to ensure proper data availability. This leads to the exclusion of seven firms due to missing FB data and a sample consisting of 23 firms and a total set of 3,284,192 firm-specific FB comments. For each firm-specific comment on FB, we gather the submission date and time (GMT+1 as related time zone). We restrict our data to comments written in English (3,194,768 comments). Since we focus on U.S. firms, the number of comments written in languages other than English is too low to serve as a proper learning set for a supervised ML algorithm (Shalev-Shwartz and Srebro 2008). We also

[5] Obtaining tweets from Twitter requires less effort and duration (Liu et al., 2012; Rao and Srivastava, 2012; Go et al., 2009), since Twitter's open API allows the collection of historical data (e.g., Rao and Srivastava, 2012; Bollen et al., 2011a; Chung and Mustafaraj, 2011; Pak and Paroubek, 2010) and special authorized third-party services, such as GNIP PowerTrack (Bartov et al., 2018) or DataSift (Driscoll and Walker, 2014) provide pay-as-you-go API access. In contrast to Twitter, FB's API is not generally accessible without requesting permission. We submitted a permission request for 'Page Public Content Access (PPCA)' that allows read-only access to public data including business metadata, posts, public comments by institutions or people and reviews, provided with a time stamp and a lot of other information (e.g., number of likes, shares or comments for the post or comment itself). The request has to include an acceptance of FB's feature usage guidelines, a detailed explanation of use case scenarios for the retrieved data, a step-by-step instruction on how the data will be retrieved and a screencast video showing the end-to-end user experience. After passing the permission process, a token provides access.

gather the firm-specific number of postings and related user shares per day. On average, our sample firms disclose 4 postings with 425 shares by FB users per day.

2.4.2 Supervised Machine Learning Approach

We employ the programming language R to develop a supervised machine learning (ML) approach using a support vector machine (SVM) to measure firm-level social media sentiment, i.e., sentiment that is transferred via comments a firm's FB post received from FB users. By using an SVM for sentiment measurement, we follow prior literature (e.g., Bartov et al. 2018; Yan, He, Shen, and Tang 2014; Zhang, Fuehres, and Gloor 2011). Bernardo, Henriques, and Lobo (2017) compare a supervised and unsupervised (keyword-based) model based on a similar dataset while classifying tweets from Twitter. They find a decrease of 12.9 percentage points in the classification error rate when using a supervised model.[6] Since social media creates its own inaccuracies and misspellings with new sentiment-related expressions from year to year, continuous learning processes are necessary to deal with these new developments. As such, a supervised ML approach yields the most accurate results for the classification of FB comments.

In contrast to other algorithms, such as the maximum entropy or Bayesian classifier, the SVM produces the most accurate results in a variety of classification problems (Agarwal, Xie, and Vovsha 2011; Li, Artemiou, and Li 2011).[7] As non-probability classifiers, SVMs operate by separating data points in space using various centerlines of the gaps separating different classes (Hutto and Gilbert 2015). Therefore, input texts are separated into 'feature vectors', which consist of both a classifiable single word and a weighting factor describing its importance (Antweiler and Frank 2004). The weight is approximated by making use of the minimum information criterion, i.e., every feature (word) is represented by a vector space that equals the corresponding feature's weight in a coordinate system. By positioning a

[6] In unsupervised sentiment analysis models, the sentiment is obtained from one variable (X) by statistical pattern analyses using lexicons or specially adjusted wordlists, i.e., most commonly the Harvard-IV wordlist. Supervised models take into account both an input variable (X) and an output variable (Y) to autonomously learn and extrapolate coherences between both variables (Ghiassi et al., 2013). While unsupervised models aim to deeply analyze and understand the structure of a given dataset, supervised models aim to approximate an input-output function so well that new data inputs are predictable with increased accuracy (Qiu et al., 2016).

[7] For example, Zhang et al. (2011) use three different ML algorithms to classify Twitter messages: Bayesian, maximum-entropy, and SVM classifier. They find that the latter algorithm predicts with the highest consistent accuracy rate. For example, Yan et al. (2014) get an accuracy level of 98.90 percent for the binary classification of Chinese and English social media sentiment using an SVM, while the usage of an N-Gram model yields only 82.42 percent.

hyperplane between the features, an objective function is calculated for optimal classification (Madge and Bhatt 2015; Pang, Lee, and Vaithyanathan 2002). SVM allows the classification of n-dimensions and is thus suitable for a classification of FB comments into a positive, negative, and neutral dimension.[8]

2.4.3 Creating Training and Test Sets

Supervised ML models are very ambitious to implement and control (Bernardo et al. 2017; Goncalves, Araújo, Benvenuto, and Cha 2013, Pang et al. 2002) since they require a manually classified subset of data to train and test the algorithms used (e.g., Bartov et al. 2018; Bollen et al. 2011b; Boiy and Moens 2009). Our SVM algorithm later extrapolates the classification features to the unclassified rest of comments, the so-called virgin dataset. Since the trained model needs to be validated against test data, we apportion a set of manually classified data into training and test sets with a 70–30 split (e.g., Birnbaum, Ernala, Rizvi, Choudhury, and Kane 2017; Ho and Ermon 2016; Usmani, Adil, Raza, and Ali 2016; Madge and Bhatt 2015; Dai and Zhang 2013). In total, we classify 34,531 FB comments by hand.[9] Validating the trained model against test data reveals, while using our SVM algorithm, an overall classification accuracy rate of 78.58 percent. In detail, the accuracy rate for the classification of positive comments is 79.92 percent, for negative comments 91.23 percent and for neutral comments 74.50 percent, respectively. The accuracy rate measures the share of comments from the test set that has been labeled as belonging to the same class by manual classification and SVM algorithm. The higher accuracy for the classification of negative than for positive or neutral comments supports the notion that negative speech is expressed more clearly and precisely, thus making it easier to detect (e.g., Mondal et al. 2017).

Moreover, we calculate the precision and recall rate of our model. The precision for a class is the number of comments correctly labeled as belonging to a certain class divided by the total number of comments labeled as belonging to this class, i.e., the sum of correctly and incorrectly classified comments. The precision for labeling comments correctly as positive, negative and neutral is 78.50 percent, 86.50 percent, and 75.50 percent, respectively. The recall rate refers to the proportion of comments within a class the algorithm correctly assigns

[8] Commonly employed binary classifiers separate positive from negative comments and calculate neutral comments as the residual sum. We do not follow this approach and follow the same classification process for neutral comments as we do for positive and negative ones.

[9] We allocate the amount of manually classified comments evenly over our final sample firms to consider firm-specific language characteristics.

to that class. It is the fraction of the relevant comments successfully retrieved. High recall values of 73 percent on average suggest that we generate a representative learning set for the language used in comments by FB users. Table 1 shows the indicated accuracy, precision, and recall rates per class, as well as the related F1 score values. The F1 score is the weighted average of precision and recall, where it reaches its best value at 100 percent and worst at 0 percent.

Table 2.1: Support Vector Machine (SVM) analytics

Classification type	Accuracy	Precision	Recall	F-Score
Positive	**79.92**	78.50	75.00	76.00
Negative	**91.23**	86.50	72.00	77.00
Neutral	**74.50**	75.50	74.00	74.00

Accuracy measures the share of comments from the test set that has been equally classified by manual classification.
Precision refers to how often a comment the algorithm predicts as belonging to a class actually belongs to that class.
Recall refers to the proportion of comments within a class the algorithm correctly assigns to that class.
F-scores produce a weighted average of both precision and recall, where the highest level of performance is equal to 100 (Japkowicz 2007).

Notes: This table provides the analytic measures calculated for the Support-Vector-Machine based sentiment classification model.

2.4.4 Pre-processing of Virgin Data

To classify the virgin data (raw data), we create three matrices that represent positive, negative, and neutral comments, respectively, for each sample firm, where each comment is accompanied by the (converted) submission time[10], yielding a total set of 75 matrices. We then run different automatic data pre-processes. Nhlabano and Lutu (2018) investigate the influence of ML-based (including SVMs) data pre-processing methods on the results of sentiment analyses for social media content. They find that intensive pre-processing leads to a reduction of dimensionality in the sample, and thus, causes an increase in the accuracy

[10] In line with Sul et al. (2014), we convert the retrieved submission time due to the market close time of 4 p.m. New York time. Any comment posted on FB after 4 p.m. was treated as day t+1. We expect the sentiment expressed later than 4 p.m. or on non-trading days (e.g., weekends, bank holidays) to influence the stock market on the following trading day.

rate. Furthermore, Wang, Pauleen, and Zhang (2016) highlight that social media content is extremely different from spoken language since it contains a high level of idiosyncratic expressions and is intensively noisy.

First, we remove URLs and email addresses (e.g., Pagolu, Reddy, Panda, and Majihi 2016; Go, Bhayani, and Huang 2009) by filtering for numbers and letters directly tied to ‘@’, punctuations,[11] and cashtags (‘$’). Second, we keep the hashtag word(s) but remove the punctuation sign ‘#’. Hashtags (‘#’) link or group the content of a comment to a certain topic that can be easily found by other social media users with the same interests (e.g., Rauschnabel, Sheldon, and Herzfeld 2019). As such, the hashtag content contributes to the expressed sentiment of a comment (e.g., Davidov et al. 2010). Third, we remove numbers and digits, stop-words (e.g., ‘the’, ‘a’, ‘and’, ‘by’), stem-words and sparse-terms (e.g., Bollen, Mao, and Zeng 2011b). Finally, the data pre-processing leads to a final sample of 2,940,252 FB comments at firm level. Table 2 shows the sample selection process.

[11] Hutto and Gilbert (2015) argue in a novel approach for creating a general sentiment classification model that punctuation increases the magnitude of intensity of sentiment expression. We do not attempt to quantify the intensity of sentiment and, in addition, this thesis holds for all three classes observed, namely ‘.’, ‘,’, ‘-’, ‘_’, ‘(’, ‘)’, ‘;’, ‘:’, ‘/’, ‘\’, ‘!’ and ‘?’. In a recent study comparing data pre-processing techniques for Twitter sentiment analyses, Effrosynidis et al. (2017) find that removing punctuation does not contribute to higher levels of classification accuracy.

Table 2.2: Sample Selection

Criterion	**Number of comments remaining**	**Percentage of comments remaining**
Firm-specific Facebook comments for 30 DJIA firms between January 1, 2009 and December 31, 2016	3,502,532	100.00
Exclusion of seven DJIA firms	3,284,192	93.77
Exclusion of non-English comments	3,194,768	91.21
Programmed automatic data pre-processing (Removal of URLs, letters and numbers linked to an @-symbol, cashtags ($), hashtags (#), numbers, digits, stop-words, stem-words, sparse-terms)	2,940,252	83.95
Final sample	2,940,252	

Notes: This table provides the sample selection and the percentage of comments remaining in the sample after data pre-processing.

2.4.5 Facebook User Sentiment

Social media communication often 'conveys information about the author's emotional state, his or her judgment or evaluation of a certain person or topic, or the intended emotional communication' (Bollen et al. 2011b, p. 4). Social media sentiment toward a firm can therefore be defined as the attitude and feelings social media users have about a firm that is present on social media (Stieglitz and Dang-Xuan 2013). Literature on social media sentiment differs between two sentiment measurements: numeric and semantic approaches. Numeric approaches use the number of messages that are linked to firms to capture how active firms are socially discussed (e.g., Mao, Wei, and Liu 2012). In contrast, semantic approaches use natural language processing (NLP) to analyze sentiment based either on wordlists or on ML models. For example, Antweiler and Frank (2004) examine the effect of more than 1.5 million messages posted on Yahoo! Finance and Raging Bull about the 45 companies in the DJIA and the Dow Jones Internet Index and measure bullishness using computational linguistics methods. They find that stock messages help predict market volatility. Bollen et al. (2011b) use a set of nine million Twitter messages and search for 65 pre-defined terms that indicate the expression of mood states. They find that these aggregated mood states are related to stock market developments. Moreover, Sul, Dennis, and Yuan (2014) examine the cumulative sentiment of 2.5 million Twitter messages by using the Harvard-IV dictionary and find a significant impact on the stock market. Using a Bayesian ML classifier, findings by Bernardo et al. (2017) provide further indications that Twitter sentiment can predict future stock prices. In addition, Bartov et al. (2018) find that the aggregate opinion from individual tweets successfully predicts a firm's forthcoming quarterly earnings and announcement returns using a Bayesian ML algorithm.

In particular, FB-related research has developed a gross national happiness (GNH) index for FB (Kramer 2010) based on users' status updates relating to the dimension of valence. Karabulut (2013) shows that FB's GNH has the ability to predict changes in both daily returns and trading volume in the U.S. stock market. Siganos, Vagenas-Nanos, and Verwijmeren (2014) examine the relation between daily sentiment and trading behavior within 20 international markets by exploiting FB's GNH. They find that sentiment has a positive contemporaneous relation to stock returns and that sentiment on Sunday affects stock returns on Monday, suggesting causality from sentiment to stock markets.

Prior studies create a sentiment index that is scaled from minus one to one, where minus one indicates negative and one indicates positive sentiment only (e.g., Mao, Counts, and Bollen 2011a; Li 2010; Das and Chen 2007). In order to enable a detailed breakdown of the effects of social media sentiment on the capital market into all three measured components, namely positive, negative and neutral sentiment, we abstain from calculating a single aggregated index. Instead, we use the firm-specific shares of comments classified as positive, negative, and neutral per day. This generates percentage values ranging from 0 to 100, with 100 indicating user comments from one sentiment class only to be passed. See Appendix 1.1 for examples of positive, negative, and neutral FB comments from our sample firms.

2.4.6 Empirical Model

2.4.6.1 Posting Passivity

To test whether a firm's social media passivity of different lengths moderates the effect of FB user sentiment on a firm's stock prices, we estimate the following regression model using firm- (Firm FE) and year-fixed (Year FE)[12] effects:

[12] We also run the main regressions with monthly and weekly fixed effects. Our main results remain unchanged. Untabulated results show significance for all but the seven-day window following the main regression patterns.

$$\mathbf{CAR_{i,[-1;+1]} = \beta_0 + \beta_1 * SENT_{i,[t\text{-}n;t\text{-}2]} + \beta_2 * PASSIVE + \beta_3 * SENT_{i,[t\text{-}n;t\text{-}2]} \times PASSIVE + AR_{i;t\text{-}2} + NEG\_NEWS_{i,t} + FOLLOWING_{i,t} + GOOGLE\_SEARCH_{i,t} + INSTITUTIONAL_{i,t} + LITIGATION_{i,t} + COMMENTS_{i,t} + POSTS_{i,t} + SHARES_{i,t} + Firm\ FE + Year\ FE + \varepsilon_{i;t}} \tag{1}$$

Our dependent variable $CAR_{i,[-1;+1]}$ is measured as adjusted abnormal returns[13] cumulated over each three-day period around the observed day. $SENT_{i,[t-n;t-2]}$ represents either the share of positive, negative, or neutral sentiment and is therefore to be replaced by $POS\_SENT_{i,[t-n;t-2]}$, $NEG\_SENT_{i,[t-n;t-2]}$ and $NEU\_SENT_{i,[t-n;t-2]}$, respectively. Our sentiment measures are measured for firm i and the period prior to the observed day [t-n; t-2] across four different trading day windows (i.e., one, three, five, and seven days preceding the CAR measurement window). Moreover, we measure user sentiment during a specific period of posting passivity, namely PASSIVE, dependent on four periods of firms' posting passivity that are consistent with our sentiment measurement window (one, three, five, and seven days). Therefore, we create the variable $PASSIVE_{peer}$ as an indicator variable that equals 1 if the firm's number of postings per day is below the sample firm's daily median, and 0 otherwise. To measure a firm's passivity compared to its historical social media posting behavior, we create the variable $PASSIVE_{hist}$ as an indicator variable that equals 1 if the firm's number of postings per day is below its daily average within the observation period. The interaction term $\beta_3 * SENT_{i,[-1;+1]} \times PASSIVE$ is our term of interest, since it measures the FB user sentiment for firms that are passive on FB for a specific period.

[13] To calculate abnormal returns, we apply a portfolio-based approach to incorporate firm-specific risk instead of simply observing the daily market average, commonly defined as $AR_t^i = R_t^i - E(R_t^{market})$ (e.g., Chen et al., 2013; Hauswald and Marquez, 2003; Chopra et al., 1992; Strong, 1992; Brickley and Schallheim, 1985; deBondt and Thaler, 1985). Specifically, following Fama and French (1995) and Kothari and Warner (2004), we compute a firm's abnormal returns by adjusting the total returns for factors that have been found to explain cross-sectional differences in stock returns, i.e., a firm's market capitalization and its book-to-market value, i.e., price-to-book value on share level. Similar to Brav et al. (2000), we form a set of floating portfolios of firms, with each portfolio expressing a distinct range of firm size, i.e., a firm's capitalization. Within each portfolio, we rank the firms by their price-to-book ratio. Based on our ranking values, we define a weighting factor $\boldsymbol{w_j}$ for each ranking position. Total returns $\boldsymbol{R_t^i}$ are adjusted by the weighted total returns with varying values for each observation day: $\boldsymbol{AR_t^i = R_t^i - R_t^{i,port}}$. Following Sul et al., (2014), we calculate $\boldsymbol{R_t^i}$ as the natural logarithm of total returns plus one: $\boldsymbol{R_t^i = ln(R_t^i + 1)}$. $\boldsymbol{R_t^{i,port}}$ therefore, can be defined as $\boldsymbol{\frac{1}{n}\sum_{j=1}^{n} w_j\,(R_t^i)}$, where the sum of weights in each portfolio equals 1 ($\boldsymbol{\sum_{j=1}^{n} w_j = 1}$).

We use a number of control variables based on prior literature. We control for abnormal returns one day prior to the measurement day of our CAR window by using $AR_{i,t-2}$ in autoregression to consider stock returns autocorrelation (Chen et al. 2014; Sul et al. 2014; Menkhoff 2010; Smirlock and Starks 1988; Kraft and Kraft 1977). We control for media penetration by measuring the strength of negative news circulated by traditional media channels (online or paper-based) by the eight U.S. news agencies with the highest daily circulation (Dow Jones Newswire, The Wall Street Journal, USA Today, The Washington Post, The New York Times, The Los Angeles Times, Business Wire and Reuters News) ($NEG\_NEWS_{i,t}$) (e.g., Bradshaw et al. 2017; Liu et al. 2018). Moreover, we control for the number of analysts following a firm's share ($FOLLOWING_{i,t}$) (e.g., Bartov et al. 2018; Chen, De, Hu, and Hwang 2013; Hong et al. 2000). To consider the impact of the overall attention a firm gets, we use the Google search volume index ($GOOGLE\_SEARCH_{i,t}$).[14] Da, Engelberg, and Gao (2011) show that Google's search volume index captures general online search behavior by population. The index provides scaled data on the relative search volume on a firm during a month. We expect high index values to be associated with high levels of sentiment, either positive or negative. Moreover, Brammer and Pavelin (2006), for example, show that the share of institutional owners is positively correlated with the probability that traders rate a stock positively. We use the percentage of institutional holdings as an additional control variable ($INSTITUTIONAL_{i,t}$). Moreover, we control for the total daily number of comments ($COMMENTS_{i,t}$). Research shows the importance of timely reactions to a crisis situation, especially by firms in an environment with fast communication where negative information is quickly disseminated (Lee et al. 2015). Jung et al. (2018) find that strategic dissemination behavior is detectable in high litigation risk firms, but not low litigation risk firms. Hence, to control for the presence of controversies that might trigger corporate actions on social media, we include an indicator variable for a firm's exposure to a high litigation risk ($LITIGATION_{i,t}$). Following Kim and Skinner (2012), our indicator equals 1 if the firm is in the biotech (SIC codes 2833-2836 and 8731-8734), computer (SIC codes 3570-3577 and 7370-7374), electronics (SIC codes 3600-3674), or retail (SIC codes 5200-5961) industries, and sales growth, abnormal return and turnover are above the sample median and size and volatility are below the sample median. We further control for the total daily number of a firm's postings ($POSTS_{i,t}$) and the number of shares generated by FB users

[14] Our results are robust to the omission of our Google search volume index variable as control variables in our main regression model.

in response to these postings ($SHARES_{i,t}$) generated. All variables are defined in Appendix 2.2.

2.4.6.2 Reactivation after Posting Passivity

To investigate the continuation and neutralization time of the moderating role of posting passivity on the relationship between FB user sentiment and future stock prices, we examine the effect of a firm's posting reactivation. Therefore, we estimate the following regression model:

$$\mathbf{CAR_{i,[-1;+1]} = \beta_0 + \beta_1 * SENT_{i,[t-n;t-2]} + \beta_2 * PASSIVE + \beta_3 * REACTIVE + \beta_4 * SENT_{i,[t-n;t-2]} \times PASSIVE + \beta_5 * SENT_{i,[t-n;t-2]} \times REACTIVE + \beta_6 * SENT_{i,[t-n;t-2]} \times PASSIVE \times REACTIVE + \Sigma\ Controls + Firm\ FE + Year\ FE + \varepsilon_{i;t}} \quad (2)$$

REACTIVE is an indicator variable that equals 1 if the daily number of posts is either above the sample's daily median after a specific period of passivity and 0 otherwise ($REACTIVE_{peer}$), or above the historical daily average number of a firm's posts after a specific period of passivity and 0 otherwise ($REACTIVE_{hist}$). In other words, it identifies reactivated posting activity by a firm on its FB business page following a specific period of posting passivity. Similar to our previous model, we observe four different trading day windows for our second indicator (i.e., one, three, five, and seven days preceding the CAR measurement window). Consequently, the observation windows for a firm's passivity are shifted backwards by the length of the observation windows for the firm's posting reactivation.

2.5 Empirical results

2.5.1 Univariate Statistics

Analyzing the comment distributions, 10.85 percent of all processed comments is classified as positive, 3.23 percent as negative, and 85.92 percent as neutral. This distribution is consistent with prior literature (e.g., Bernardo et al. 2017; Sul et al. 2014; Go et al. 2009). We find, in total, more positive than negative comments on the sample firms' FB posts. Only some firms (e.g., ExxonMobil, Travelers Companies, Procter and Gamble, and Verizon) receive more negative than positive comments from FB users.

Table 3 provides descriptive statistics for all variables in our main regression model specifications. All variables are winsorized at the 1st and 99th percentile to mitigate the influence of outliers. The mean value for our sentiment measures POS_SENT, NEG_SENT and NEU_SENT are 21.20, 6.99, and 71.80 percent, respectively. This coincides with the distribution of FB comments. The mean value for our CAR measure is 0.001. The average share of passive firms and firms resuming their posting activity per day is 67.90 percent and 16.50 percent, respectively. On average, approximately two negative news publications occur in traditional media per day (NEG_NEWS) and a firm is followed by 26 analysts (FOLLOWING). The mean share of institutional owners is 78.68 percent (INSTITUTIONAL), indicating a high coverage of institutional holdings. On average, our sample firms release one post per day (POSTS) and receive approximately 44 comments per day (COMMENTS). The daily mean of user shares is 236.489, which means that a post is shared, on average, 236 times by FB users (SHARES).

Table 4 presents the Pearson-Spearman correlations. POS_SENT is significantly negatively correlated with NEG_SENT (Pearson -0.178; Spearman -0.111) and negatively with NEU_SENT (Pearson -0.745; Spearman -0.744). Our variable CAR shows a significant and negative correlation with NEG_SENT (Pearson -0.016, Spearman 0.000), which is the first indication that negative user sentiment on FB negatively affects the capital market. Our two variables reflecting a firm's passivity, i.e., $PASSIVE_{peer}$ and $PASSIVE_{hist}$ show a significant and strong positive correlation (Pearson 0.465, Spearman 0.621). This is a first indication that our sample firm's social media activity is indeed linked to the activity of the peer group. Thus, our assumption of homogenous social media activity among firms that operate in an already rich information environment is supported. $PASSIVE_{peer}$ is significantly positively correlated with NEG_SENT (Pearson 0.145, Spearman 0.142), pointing toward a restraint in firms' posting activity in the event of negative user sentiment. This correlation is stronger for $PASSIVE_{hist}$ (Pearson 0.225, Spearman 0.142).

Table 2.3: Descriptive Statistics

Variable	Mean	Std.	Min.	25%	Median	75%	Max.
CAR	0.001	0.023	-0.344	-0.009	0.002	0.013	0.506
POS_SENT	21.203	28.300	0.000	0.000	10.813	31.395	100.000
NEG_SENT	6.997	19.905	0.000	0.000	0.000	0.000	100.000
NEU_SENT	71.800	31.727	0.000	56.522	81.818	100.000	100.000
$PASSIVE_{peer}$	0.679	0.466	0.000	0.000	1.000	1.000	1.000
$PASSIVE_{hist}$	0.496	0.158	0.000	0.000	0.000	1.000	1.000
REACTIVE	0.165	0.371	0.000	0.000	0.000	0.000	1.000
AR	0.000	0.013	-0.221	-0.005	0.000	0.006	0.213
NEG_NEWS*	2.296	5.108	0.000	0.000	0.000	2.000	67.000
FOLLOWING*	25.734	7.570	14.000	20.000	24.000	29.000	50.000
GOOGLE_SEARCH	64.020	16.738	29.000	52.000	63.000	77.000	100.000
INSTITUTIONAL	78.680	22.858	0.580	76.760	84.570	94.290	99.960
LITIGATION	0.089	0.285	0.000	0.000	0.000	0.000	1.000
COMMENTS*	43.750	3770.716	0.000	0.000	0.000	4.000	874863
POSTS*	1.446	0.898	0.000	1.000	1.000	2.000	31.000
SHARES*	236.488	1785.263	0.000	5.000	21.000	75.000	130714.000

Notes: This table provides descriptive statistics of the full sample for all variables. For clarity, asterisked variables show descriptive statistics for the variable's winsorized raw data instead of logarithmized data as used in our regression models. Please see Appendix 2.2 for variable definitions.

Interestingly, the share of negative news in traditional media (NEG_NEWS) is significantly positively correlated to the number of analysts following a firm (FOLLOWING) (Pearson 0.212; Spearman 0.269). Moreover, NEG_NEWS is significantly negatively correlated to NEG_SENT (Pearson -0.052, Spearman -0.055). This is a first indicator that the sentiment expressed in traditional news media differs from social media sentiment, and its impact on stock markets needs to be treated differently and independently in financial analyses. COMMENTS is not significantly correlated with any other variable. However, since COMMENTS represents the total number of comments instead of an aggregated measure on a daily basis with differing positive, negative, and neutral user sentiment, this is not surprising and highlights the need of including user sentiment transferred by comments into capital market considerations. However, as expected, the number of user comments (COMMENTS) significantly correlates with the number of firm-generated posts (POSTS) (Pearson 0.140; Spearman 0.119) and the number of user shares (SHARES) (Pearson 0.235;

Spearman 0.450). Overall, the absence of high correlations among our variables suggests that there are no multi-collinearity concerns.

Table 2.4: Pearson-Sperman-Correlations

Variable	$CAR_{[-1;+1]}$	POS_SENT	NEG_SENT	NEU_SENT	$PASSIVE_{peer}$	$PASSIVE_{hist}$	RESUMP-TION	$AR_{[t-2]}$	NEG_NEWS	FOLLOWING	GOOGLE_SEARCH	INSTITU-TIONAL	LITI-GATION	COM-MENTS	POSTS	SHARES
CAR		-0.003	**-0.016**	0.013	-0.007	-0.014	-0.006	**0.706**	-0.009	-0.003	0.002	0.009	-0.004	**0.021**	0.007	-0.008
POS_SENT	0.008		**-0.111**	**-0.744**	**-0.092**	**-0.124**	0.027	0.008	**0.058**	**-0.059**	0.012	**0.086**	0.003	**0.157**	**0.069**	**-0.047**
NEG_SENT	0.000	**-0.178**		**-0.392**	**0.145**	**0.225**	**0.045**	0.007	**-0.052**	**0.199**	**0.114**	0.003	0.004	**0.211**	**-0.041**	**0.054**
NEU_SENT	0.004	**-0.745**	**-0.524**		0.025	0.001	**0.069**	0.000	**0.014**	-0.003	0.002	**-0.100**	-0.010	0.013	-0.008	**0.037**
$PASSIVE_{peer}$	-0.001	**-0.139**	**0.076**	**0.048**		**0.465**	**0.129**	-0.009	**-0.044**	**0.217**	**0.065**	**-0.042**	0.027	**0.344**	**-0.120**	**-0.067**
$PASSIVE_{hist}$	-0.012	**-0.023**	**0.142**	**0.001**	**0.621**		**0.223**	-0.007	**-0.051**	**0.126**	**0.041**	**-0.002**	0.014	**0.241**	**-0.095**	**-0.110**
REACTIVE	-0.009	**-0.074**	**-0.066**	**0.113**	**0.129**	**0.096**		-0.000	-0.021	**0.081**	**0.062**	**-0.098**	0.014	**0.332**	**0.100**	**0.502**
AR	**0.735**	-0.003	-0.011	0.010	-0.007	-0.013	0.0078		-0.004	-0.002	0.004	0.000	0.000	**0.017**	0.001	-0.001
NEG_NEWS	**-0.015**	0.012	**-0.055**	**0.027**	**-0.028**	**-0.016**	-0.001	-0.013		**0.269**	**-0.091**	**0.047**	**-0.017**	**0.040**	**0.031**	**-0.061**
FOLLOWING	**-0.015**	**-0.083**	**0.044**	**0.042**	**0.133**	**0.265**	**0.060**	-0.005	**0.212**		**0.097**	**-0.03**	**-0.063**	**0.147**	**-0.082**	**0.153**
GOOGLE_SEARCH	0.005	**-0.092**	0.006	**0.076**	**0.066**	**0.103**	**0.053**	0.004	**-0.094**	**0.050**		**0.122**	**-0.221**	**0.343**	**0.031**	**0.142**
INSTITUTIONAL	-0.005	**0.050**	**0.041**	**-0.071**	**-0.086**	**-0.063**	**-0.111**	-0.013	**0.046**	**0.015**	**0.074**		**-0.295**	0.000	0.000	**-0.074**
LITIGATION	-0.007	**0.030**	-0.008	**-0.021**	0.0275	0.026	0.014	-0.004	**-0.026**	**-0.067**	**-0.209**	**-0.292**		-0.004	**0.051**	0.002
COMMENTS	0.001	-0.007	-0.004	0.009	**-0.046**	**-0.014**	**0.105**	0.002	0.002	0.004	0.005	**-0.015**	**-0.086**		**0.119**	**0.450**
POSTS	0.009	**0.045**	**-0.084**	0.014	**-0.126**	**-0.198**	**0.093**	0.003	0.009	**-0.058**	**0.018**	0.014	**0.055**	**0.140**		**0.144**
SHARES	0.004	**-0.062**	**-0.045**	**0.085**	**0.074**	**0.034**	**0.135**	0.006	**-0.035**	**0.057**	**0.148**	**-0.091**	**-0.029**	**0.235**	**0.082**	

Notes: This table represents Pearson-Spearman correlations. Measures above and below the diagonal represent Spearman and Pearson correlations, respectively. Correlations among the sentiment measures are highlighted in the upper left section. Bold values mark coefficients that are significant at p < 0.05. All variables are winsorized at the 1st and 99th percentiles.

2.5.2 Stock Returns, Facebook Sentiment and Posting Passivity

First, we examine whether and how timely the capital market reacts to a firm's temporary social media passivity. Table 5 represents our main regression results for Equation 1, examining the overall impact of firms' daily FB user sentiment measured separately across four periods (one, three, five, and seven days) on future stock market returns dependent on four periods of firms' posting passivity (one, three, five, and seven days) relative to their peers (Panel A) or relative to their historical social media activity (Panel B). In other words, we measure user sentiment during a specific period of posting passivity and examine how this absence from social media, i.e., from FB, affects the relationship between user sentiment and future stock market returns by examining the interaction term between one of our three sentiment measures and our variables $PASSIVE_{peer}$ and $PASSIVE_{hist}$. Specifically, this interaction term represents the incremental effect of FB user sentiment on our dependent variable, i.e., the three-day CAR window, for firms exhibiting posting passivity during a specific period.

We first interpret our results using $PASSIVE_{peer}$ (Panel A). For our positive sentiment measure, we find a significant and positive coefficient for the three-, five- and seven-day window, indicating that positive sentiment on FB is likely to predict positive stock returns in the future. However, the coefficients on the interaction terms with our passivity variable are significant and negative for the five- and seven-day window. Importantly, the magnitude of the interaction terms' coefficients exceeds the coefficient of the main term. This means that a longer period of passivity by a firm, starting from a five-day period, is likely to reverse the positive effect of positive social media sentiment. In other words, FB users seem to penalize a firm's posting passivity on FB after a few days.

For our negative measure, we find a significant and negative coefficient across all time windows, indicating that negative sentiment is associated with negative future stock returns. These findings are congruent with prior studies (e.g., Bartov et al. 2018). Again, our interaction with the passivity variable is our term of interest and we find a highly significant and negative coefficient for the five- and seven-day window. In contrast to positive user sentiment, we do not find a turnaround of the coefficient's sign but instead a boosting negative effect for the seven-day window displayed by the magnitude of the coefficient. This finding indicates that, for example, a firm's passivity period of one week gives rise to negative sentiment even worse in terms of its negative effect on the firm's future stock prices.

In conclusion, posting passivity on FB, at least for firms in a highly dynamic information environment, such as DJIA firms, seems to cause future negative stock prices.

Interpreting our results using $PASSIVE_{hist}$ (Panel B), we find no significant divergence in the directions of effects compared to using $PASSIVE_{peer}$. Recalling the positive correlation between both variables, this seems rational. However, when relating a firm's posting activity to its historical posting average by using $PASSIVE_{hist}$, the magnitude of the effects is stronger within the entirety of our results. One way to interpret this fact is to assume that investors' perception of a firm's social media passivity is a two-stage process. Considering the efforts and transaction costs of continuously comparing the information disclosure behavior (including social media communication) of firms to their peers, investors may initially recognize changes in the posting activity of the firms they invested in. More specifically, they most likely compare the firm's own social media activity over time. In a second stage and more subtly, divergences in comparison with peer firms are recognized. Hence, as supported by our correlation and regression analyses, the effects of social media passivity on abnormal returns manifest more clearly when using historical social media activity as a reference.

One must consider that although social media sentiment is available in real time, stock traders need some time to adopt the sentiment expressed by FB users. This is in line with the theory of herding and the wisdom of crowds. The results indicate that social media sentiment toward firms appears to have a manifestation time of at least three days until traders on the stock market process and consider social media sentiment in their investment decisions. Unsurprisingly, we find no significant relationships between neutral social media sentiment toward a firm and future stock prices regardless of the posting behavior of a firm.

Regarding our control variables, we find that the coefficient on NEG_NEWS is highly significant and negatively associated with CARs across all four time windows. This supports prior findings on the importance of traditional news media in stock market prediction (e.g., Allen, McAleer, and Singh 2019; Veronesi 1999). In line with prior literature, we find that the coefficient on INSTITUTIONAL is highly significant and negatively related to CAR (e.g., Bartov et al. 2018). The adjusted R^2 varies between 4.4 and 5.5 percent.[15]

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[15] These adjusted R^2 values of our model exhibit even higher explanation levels than in prior studies (e.g., Bartov et al., 2018; Sul et al., 2014; Chen et al., 2013; Bollen et al., 2011b; Tetlock et al., 2008; Tetlock, 2007).

Table 2.5 Panel A: Facebook sentiment, posting passivity relative to a firm's peers and CAR

Dependent Variable=	[1-Day] SENT[-2]; PASSIVE$_{peer}$ [-2]			[3-Day] SENT[-4;-2]; PASSIVE$_{peer}$ [-4;-2]			[5-Day] SENT[-6;-2]; PASSIVE$_{peer}$ [-6;-2]			[7-Day] SENT[-8;-2]; PASSIVE$_{peer}$ [-8;-2]		
CAR[-1;+1]	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
POS_SENT	-0.000			0.008*			0.010*			0.016*		
	(-0.070)			(1.822)			(1.707)			(1.824)		
POS_SENT x PASSIVE$_{peer}$	0.010			-0.006			-0.015**			-0.023**		
	(0.630)			(-0.179)			(-2.252)			(-2.509)		
NEG_SENT		-0.014*			-0.028*			-0.037**			-0.052**	
		(-1.928)			(-1.806)			(-2.440)			(-2.037)	
NEG_SENT x PASSIVE$_{peer}$		-0.000			0.027			-0.036**			-0.125***	
		(-0.012)			(0.689)			(-2.097)			(-3.449)	
NEU_SENT			0.005			0.003			0.006			0.032
			(1.215)			(0.346)			(0.470)			(1.001)
NEU_SENT x PASSIVE$_{peer}$			-0.006			-0.006			-0.006			-0.026
			(-0.451)			(-0.223)			(-0.167)			(-0.560)
PASSIVE$_{peer}$	0.589	0.783	1.238	0.671	0.404	1.058	0.756	0.344	1.041	0.407	0.121	2.482
	(1.083)	(1.569)	(1.069)	(0.890)	(0.651)	(0.462)	(0.837)	(0.502)	(0.336)	(0.384)	(0.163)	(0.651)
AR[t-2]	438.024***	437.793***	438.075***	463.986***	463.579***	463.985***	487.092***	486.769***	487.141***	465.421***	464.997***	465.001***
	(37.379)	(37.362)	(37.386)	(33.754)	(33.718)	(33.752)	(32.385)	(32.361)	(32.388)	(28.798)	(28.770)	(28.772)
NEG_NEWS	-0.578***	-0.577***	-0.578***	-0.603***	-0.599***	-0.599***	-0.596***	-0.590***	-0.590***	-0.533**	-0.538**	-0.527**
	(-3.544)	(-3.536)	(-3.540)	(-3.083)	(-3.068)	(-3.066)	(-2.773)	(-2.745)	(-2.746)	(-2.256)	(-2.281)	(-2.234)
FOLLOWING	-1.330	-1.210	-1.345	-2.100	-1.904	-2.138	-2.840*	-2.542	-2.839*	-2.631	-2.049	-2.366
	(-1.022)	(-0.929)	(-1.034)	(-1.336)	(-1.208)	(-1.361)	(-1.657)	(-1.477)	(-1.658)	(-1.413)	(-1.094)	(-1.273)
GOOGLE_SEARCH	-0.639	-0.604	-0.636	-1.107	-1.026	-1.119	-1.395	-1.273	-1.405	-1.655	-1.390	-1.559
	(-0.876)	(-0.826)	(-0.870)	(-1.268)	(-1.171)	(-1.281)	(-1.448)	(-1.316)	(-1.457)	(-1.564)	(-1.305)	(-1.472)
INSTITUTIONAL	-0.052**	-0.052**	-0.052**	-0.066***	-0.066***	-0.066***	-0.077***	-0.078***	-0.078***	-0.089***	-0.090***	-0.090***
	(-2.520)	(-2.510)	(-2.526)	(-2.861)	(-2.876)	(-2.865)	(-3.233)	(-3.266)	(-3.242)	(-3.523)	(-3.572)	(-3.559)
LITIGATION	-0.733	-0.700	-0.720	-0.384	-0.307	-0.380	-0.285	-0.177	-0.275	-0.514	-0.350	-0.417
	(-1.292)	(-1.233)	(-1.269)	(-0.567)	(-0.454)	(-0.562)	(-0.392)	(-0.242)	(-0.377)	(-0.662)	(-0.448)	(-0.536)
COMMENTS	-0.386***	-0.361***	-0.379***	-0.230*	-0.198	-0.231*	-0.156	-0.120	-0.160	-0.319**	-0.253*	-0.297*
	(-3.278)	(-3.045)	(-3.209)	(-1.720)	(-1.467)	(-1.722)	(-1.098)	(-0.832)	(-1.123)	(-2.098)	(-1.646)	(-1.960)
POSTS	0.402**	0.386**	0.399**	0.492***	0.472**	0.499***	0.348*	0.323	0.357*	0.389*	0.333	0.376*
	(2.511)	(2.405)	(2.490)	(2.616)	(2.504)	(2.649)	(1.687)	(1.559)	(1.733)	(1.719)	(1.467)	(1.661)
SHARES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.065)	(1.029)	(1.037)	(0.994)	(0.919)	(0.954)	(1.015)	(0.923)	(0.962)	(1.233)	(1.185)	(1.146)
Constant	12.398**	11.919**	12.037**	17.692***	17.030***	17.792***	22.376***	21.302***	22.173***	24.213***	21.206***	20.258***
	(2.422)	(2.330)	(2.351)	(2.954)	(2.838)	(2.953)	(3.469)	(3.290)	(3.395)	(3.474)	(3.024)	(2.859)
Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	30,995	30,995	30,995	22,380	22,380	22,380	18,478	18,478	18,478	16,042	16,042	16,042
Number of firms	23	23	23	23	23	23	23	23	23	23	23	23
Adj. R2	0.0439	0.0440	0.0440	0.0492	0.0493	0.0492	0.0546	0.0548	0.0546	0.0504	0.0507	0.0506

*Notes: This table reports the regression results for the association between positive (POS_SENT), negative (NEG_SENT) or neutral (NEU_SENT) FB user sentiment and a firm's cumulative abnormal returns (CAR) dependent on a firm's posting passivity (PASSIVEpeer). POS_SENT (NEG_SENT, NEU_SENT) is the firm-specific share of comments classified as positive (negative, neutral) sentiment within the different time windows. PASSIVEpeer indicates low posting activity on a firm's Facebook business page and equals 1 if the firm's number of postings is below the sample's daily median, and zero otherwise. Our variable of interest is the interaction term between FB user sentiment and PASSIVE. CAR is measured for the three days around the observation day [t-1; t; t+1]. See Appendix 2.2 for all variable definitions. Models I to XII report the results for positive sentiment (POS_SENT), negative sentiment (NEG_SENT) and neutral sentiment (NEU_SENT) for each of the four time windows [1-Day, 3-Day, 5-Day, 7-Day] a firm exhibits continuous posting passivity, respectively. Models are estimated using OLS regression with firm and year fixed effects (FE). All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at the client level are presented in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels based on two-tailed tests.*

Table 2.5 Panel B: Facebook sentiment, posting passivity relative to a firm's historical posting activity and CAR

Dependent Variable=	[1-Day] SENT[-2]; PASSIVE$_{hist}$ [-2]			[3-Day] SENT[-4;-2]; PASSIVE$_{hist}$ [-4;-2]			[5-Day] SENT[-6;-2]; PASSIVE$_{hist}$ [-6;-2]			[7-Day] SENT[-8;-2]; PASSIVE$_{hist}$ [-8;-2]		
CAR[-1;+1]	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
POS_SENT	-0.002			0.002*			0.008**			0.024*		
	(-0.016)			(1.856)			(2.325)			(1.884)		
POS_SENT x PASSIVE$_{hist}$	0.000			-0.012			-0.024*			-0.059***		
	(1.165)			(-0.036)			(-1.864)			(-3.871)		
NEG_SENT		-0.021*			-0.036**			-0.069**			-0.078**	
		(-1.781)			(-2.002)			(-2.498)			(-2.355)	
NEG_SENT x PASSIVE$_{hist}$		-0.002			0.035			-0.069**			-0.198***	
		(-1.143)			(0.223)			(-2.388)			(-2.988)	
NEU_SENT			0.000			0.000			0.001			0.013
			(1.002)			(1.175)			(1.662)			(1.035)
NEU_SENT x PASSIVE$_{hist}$			-0.001			-0.001			-0.003			-0.008
			(-0.916)			(-1.153)			(-0.896)			(-0.863)
PASSIVE$_{hist}$	0.576	0.583	0.474	1.025*	1.071*	1.406	0.504	0.785	0.635	0.786	1.041*	0.576
	(0.895)	(0.995)	(0.352)	(1.687)	(1.929)	(1.100)	(0.839)	(1.425)	(0.497)	(1.229)	(1.792)	(0.895)
AR[t-2]	409.941***	409.729***	409.957***	412.883***	412.705***	412.874***	406.671***	406.460***	406.705***	474.735***	474.544***	409.941***
	(32.953)	(32.938)	(32.956)	(33.774)	(33.760)	(33.775)	(33.442)	(33.428)	(33.447)	(39.002)	(38.990)	(32.953)
NEG_NEWS	-0.622***	-0.619***	-0.621***	-0.658***	-0.658***	-0.657***	-0.567***	-0.564***	-0.566***	-0.510***	-0.508***	-0.622***
	(-3.603)	(-3.585)	(-3.593)	(-3.876)	(-3.876)	(-3.871)	(-3.347)	(-3.331)	(-3.342)	(-3.015)	(-3.001)	(-3.603)
FOLLOWING	-1.579	-1.398	-1.565	-1.373	-1.261	-1.350	-1.266	-1.140	-1.270	-1.861	-1.749	-1.579
	(-1.134)	(-1.004)	(-1.125)	(-1.002)	(-0.920)	(-0.986)	(-0.926)	(-0.833)	(-0.930)	(-1.362)	(-1.280)	(-1.134)
GOOGLE_SEARCH	-0.389	-0.343	-0.371	-0.193	-0.170	-0.180	-0.399	-0.356	-0.392	-0.150	-0.114	-0.389
	(-0.505)	(-0.445)	(-0.482)	(-0.254)	(-0.224)	(-0.238)	(-0.527)	(-0.470)	(-0.517)	(-0.198)	(-0.151)	(-0.505)
INSTITUTIONAL	-0.054**	-0.053**	-0.054**	-0.057**	-0.057**	-0.057**	-0.054**	-0.053**	-0.054**	-0.042*	-0.042*	-0.054**
	(-2.354)	(-2.320)	(-2.351)	(-2.530)	(-2.516)	(-2.525)	(-2.382)	(-2.372)	(-2.396)	(-1.877)	(-1.863)	(-2.354)
LITIGATION	-0.917	-0.877	-0.897	-1.195**	-1.175**	-1.182**	-0.982*	-0.953	-0.967	-1.263**	-1.227**	-0.917
	(-1.527)	(-1.460)	(-1.493)	(-2.023)	(-1.989)	(-2.001)	(-1.665)	(-1.615)	(-1.639)	(-2.140)	(-2.078)	(-1.527)
COMMENTS	-0.406***	-0.377***	-0.392***	-0.379***	-0.364***	-0.370***	-0.379***	-0.355***	-0.370***	-0.422***	-0.395***	-0.406***
	(-3.218)	(-2.970)	(-3.103)	(-3.059)	(-2.921)	(-2.981)	(-3.078)	(-2.862)	(-2.997)	(-3.384)	(-3.150)	(-3.218)
POSTS	0.387**	0.371**	0.381**	0.410**	0.401**	0.406**	0.413**	0.397**	0.408**	0.481***	0.465***	0.387**
	(2.324)	(2.229)	(2.290)	(2.504)	(2.449)	(2.482)	(2.531)	(2.434)	(2.499)	(2.938)	(2.840)	(2.324)
SHARES	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.219)	(1.175)	(1.183)	(0.947)	(0.931)	(0.923)	(1.137)	(1.111)	(1.114)	(1.368)	(1.328)	(1.219)
Constant	12.464**	11.651**	11.721**	11.229**	10.720**	10.605*	11.368**	10.797**	10.947**	11.249**	10.807**	11.007**
	(2.252)	(2.107)	(2.118)	(2.062)	(1.969)	(1.946)	(2.093)	(1.988)	(2.014)	(2.071)	(1.990)	(2.025)

Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	30,995	30,995	30,995	22,380	22,380	22,380	18,478	18,478	18,478	16,042	16,042	16,042
Number of firms	23	23	23	23	23	23	23	23	23	23	23	23
Adj. R2	0.0377	0.0378	0.0378	0.0397	0.0397	0.0397	0.0388	0.0389	0.0389	0.0521	0.0522	0.0521

*Notes: This table reports the regression results for the association between positive (POS_SENT), negative (NEG_SENT) or neutral (NEU_SENT) FB user sentiment and a firm's cumulative abnormal returns (CAR) dependent on a firm's posting passivity (PASSIVEhist). POS_SENT (NEG_SENT, NEU_SENT) is the firm-specific share of comments classified as positive (negative, neutral) sentiment within the different time windows. PASSIVEhist indicates low posting activity on a firm's Facebook business page and equals 1 if the firm's number of postings is below its historical daily average, and zero otherwise. Our variable of interest is the interaction term between FB user sentiment and PASSIVE. CAR is measured for the three days around the observation day [t-1; t; t+1]. See Appendix 2.2 for all variable definitions. Models I to XII report the results for positive sentiment (POS_SENT), negative sentiment (NEG_SENT) and neutral sentiment (NEU_SENT) for each of the four time windows [1-Day, 3-Day, 5-Day, 7-Day] a firm exhibits continuous posting passivity, respectively. Models are estimated using OLS regression with firm and year fixed effects (FE). All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at the client level are presented in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels based on two-tailed tests.*

2.5.3 Stock Returns, Facebook Sentiment and Posting Reactivation

Second, we ask what happens when the firm restarts posting on FB. Specifically, we are interested in examining how long the negative effects of posting passivity last when the firm is posting new content on its business page after a period of passivity. Prior literature shows that negative and positive investor sentiment, evoked by the processing of bad and good news, are asymmetrically affecting stock prices, with negative sentiment causing market overreactions for a short period of time (e.g., Veronesi 1999; Barberis, Shleifer, and Vishny 1998; Howe 1986). This particularly raises the question if the incremental negative effects of both positive and negative social media sentiment on future stock prices—due to posting passivity—exhibit different neutralization times in the event of a posting reactivation. How long does it take until the firm can overcome these negative effects by resuming its posting activity? We refer to this as ‘neutralization time’ below.

To examine this question, we introduce different time windows for the firm’s reactivation of posting activity after a certain period of passivity. Estimating Equation 1, our regression results reveal that a passivity period of one or three days does not affect the association between a firm’s user sentiment and future stock prices. Consequently, we do not include a previous posting passivity of one or three days and focus on a passivity period of five and seven days, instead. We combine our two time windows for measuring the firm’s posting passivity with four time windows for the firm’s posting reactivation, that is, a continuous period of new posting activity. We shift the two observation windows for posting passivity backwards by the length of the observation windows for reactivated posting activity. As before, we consider two methods of measuring passivity, i.e., relative to a firm’s peers ($\text{PASSIVE}_{\text{peer}}$) or relative to a firm’s historical posting activity ($\text{PASSIVE}_{\text{hist}}$). However, due to coherent results, we restrict our discussion to results for $\text{PASSIVE}_{\text{peer}}$. In line with that, we use $\text{REACTIVE}_{\text{peer}}$ to measure resuming posting activity. Table 6 represents our main regression results for Equation 2, examining the overall impact of firms’ daily FB user sentiment measured separately across two periods (five and seven days) on future stock market returns dependent on four periods of posting reactivation (one, three, five, and seven days) after two periods of firms’ posting passivity (five and seven days). Our term of interest is the three-way interaction term between each of our three sentiment measures, our variable $\text{PASSIVE}_{\text{peer}}$ and our variable $\text{REACTIVE}_{\text{peer}}$.

Table 6, Panel A, and Table 6, Panel B, show the regression results for a five-day and seven-day posting passivity, respectively. We find significant and positive coefficients on our positive sentiment measure, for a new posting period of one and three days. For a seven-day period of new posting passivity, we find this positive effect to be significant until the five-day period. The coefficients on the three-way interaction term are significant and positive for the one-day and three-day window of posting reactivation, respectively. These findings are a first indication that the longer the firm is passive on FB, the longer the firm takes to overcome the negative effects of the posting passivity with new FB postings. In other words, the neutralization time corresponds with the length of the firm's posting passivity.

For our negative sentiment measure, we find significant and negative coefficients until a period of posting reactivation of five days (seven days) for a passivity of five days (seven days). Similarly, the coefficients on the three-way interaction term are significant and positive until the three-day (five-day) period of new posting activity after a passivity of five days (seven days). However, the magnitude of the coefficient for the last time windows is weak. Nonetheless, the negative effect seems to be neutralized after a new posting activity over five to seven days. For our neutral sentiment measure, we find no significant relationship between neutral sentiment and future stock returns for five days of passivity, as well as for its related three-way interaction term. However, we find a significant and positive relationship when the firm is passive for a week. It seems as if the posting reactivation of the firm after a period of neutral user sentiment on FB during a period of the firm's posting passivity can turn quickly into a value added for the firm. Since neutral sentiment measurement during a period of posting passivity is based on the comments on a firm's FB post in the past, this means that the firm is still at the heart of FB users and thus under discussion.

Our results are validated with the slope difference test by Dawson and Richter (2006). In addition, we calculate the marginal effects of our sentiment measures and our two indicator variables for values of half a standard deviation (SD) below and above the mean and receive significant results ($p < 0.05$).

Table 2.6 Panel A: Posting reactivation and five-day posting passivity

Dependent Variable= CAR [-1;+1]	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
		[1-Day] REACTIVE$_{peer}$ [-2]			[3-Day] REACTIVE$_{peer}$ [-4;-2]			[5-Day] REACTIVE$_{peer}$ [-6;-2]			[7-Day] REACTIVE$_{peer}$ [-8;-2]	
POS_SENT	0.010*			0.012*			0.014			0.008		
	(1.928)			(1.925)			(0.948)			(0.512)		
POS_SENT x PASSIVE$_{peer}$	-0.019**			-0.023**			-0.029**			-0.036**		
	(-2.914)			(-1969)			(-1.970)			(-2.213)		
POS_SENT x REACTIVE$_{peer}$	0.001			0.000			0.001			0.001		
	(0.170)			(0.130)			(1.448)			(1.298)		
POS_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$	0.015**			0.003			0.004			0.035		
	(2.441)			(0.059)			(0.070)			(0.608)		
NEG_SENT		-0.043**			-0.035**			-0.037*			-0.038*	
		(-2.251)			(-2.173)			(-1.698)			(-1.775)	
NEG_SENT x PASSIVE$_{peer}$		-0.091***			-0.051**			-0.055**			-0.080*	
		(-2.717)			(-2.223)			(-2.223)			(-2.360)	
NEG_SENT x REACTIVE		0.069			0.090			0.102			0.065	
		(1.030)			(1.168)			(1.031)			(1.299)	
NEG_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$		0.077***			0.037**			0.042			0.044	
		(3.410)			(2.172)			(0.764)			(0.751)	
NEU_SENT			0.008			0.003			0.002			0.008
			(0.586)			(0.270)			(0.172)			(0.619)
NEU_SENT x PASSIVE$_{peer}$			0.047			0.002			0.000			0.000
			(1.030)			(0.083)			(0.077)			0.040)
NEU_SENT x REACTIVE			0.000			0.000			0.001			0.001
			(0.983)			(0.900)			(1.038)			(1.166)
NEU_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$			0.030			0.013			0.015			0.001
			(0.670)			(0.309)			(0.368)			(0.016)
CONTROLS	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	22.673***	21.528***	22.272***	22.299***	21.454***	22.445***	22.286***	21.547***	22.682***	23.485***	22.151***	22.865***
	(3.241)	(3.063)	(3.143)	(3.233)	(3.099)	(3.215)	(3.251)	(3.132)	(3.272)	(3.433)	(3.226)	(3.304)
Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	16,852	16,852	16,852	16,830	16,830	16,830	16,787	16,787	16,787	16,785	16,785	16,785
Adj. R2	0.0482	0.0485	0.0483	0.0510	0.0511	0.0510	0.0480	0.0481	0.0480	0.0659	0.0660	0.0658

Table 2.6 Panel B: Posting reactivation and seven-day posting passivity

Dependent Variable= CAR [-1;+1]	[1-Day] REACTIVE$_{peer}$ [-2] I	II	III	[3-Day] REACTIVE$_{peer}$ [-4;-2] IV	V	VI	[5-Day] REACTIVE$_{peer}$ [-6;-2] VII	VIII	IX	[7-Day] REACTIVE$_{peer}$ [-8;-2] X	XI	XII
POS_SENT	0.019*			0.015*			0.015*			-0.019		
	(1.823)			(1.697)			(1.691)			(-0.989)		
POS_SENT x PASSIVE$_{peer}$	-0.029**			-0.036**			-0.040**			-0.038**		
	(-2.289)			(-2.293)			(-2.288)			(-2.232)		
POS_SENT x REACTIVE$_{peer}$	0.053			0.004			0.002			0.002		
	(0.480)			(0.568)			(0.025)			(0.036)		
POS_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$	0.023*			0.015*			0.003			0.027		
	(1.677)			(1.781)			(0.042)			(0.352)		
NEG_SENT		-0.056**			-0.048*			-0.051**			-0.048*	
		(-2.047)			(-1.766)			(-2,171)			(-1.800)	
NEG_SENT x PASSIVE$_{peer}$		-0.128***			-0.196***			-0.280***			-0.269**	
		(-3.329)			(-4.989)			(-3.380)			(-4.859)	
NEG_SENT x REACTIVE$_{peer}$		-0.026*			-0.133			-0.123			-0.113	
		(-1.755)			(-0.988)			(-0.718)			(-0.029)	
NEG_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$		0.089***			0.058**			0.051*			0.060	
		(3.458)			(2.170)			(1.789)			(0.867)	
NEU_SENT			0.035**			0.029*			0.029*			0.031*
			(2.084)			(1.763)			(1.812)			(1.947)
NEU_SENT x PASSIVE$_{peer}$			0.022			0.008			0.012			0.029
			(0.035)			(0.719)			(1.071)			(1.084)
NEU_SENT x REACTIVE$_{peer}$			0.002			0.003			0.000			0.000
			(1.468)			(1.368)			(0.030)			(0.028)
NEU_SENT x PASSIVE$_{peer}$ x REACTIVE$_{peer}$			0.060			0.036			0.026			0.018
			(1.095)			(0.702)			(0.514)			(0.334)
CONTROLS	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	26.050***	22.964***	21.770***	24.460***	21.834***	20.906***	24.331***	21.501***	20.684***	25.577***	22.482***	21.378***
	(3.443)	(3.015)	(2.832)	(3.286)	(2.915)	(2.764)	(3.286)	(2.886)	(2.751)	(3.468)	(3.030)	(2.856)
Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	14,593	14,593	14,593	14,572	14,572	14,572	14,543	14,543	14,543	14,550	14,550	14,550
Adj. R2	0.0433	0.0436	0.0436	0.0467	0.0469	0.0469	0.0436	0.0438	0.0438	0.0614	0.0615	0.0616

*Notes: This table reports the regression results for the association between positive (POS_SENT), negative (NEG_SENT) or neutral (NEU_SENT) FB user sentiment and a firm's cumulative abnormal returns (CAR) dependent on a firm's posting reactivation (REACTIVEpeer) following a period of posting passivity (PASSIVEpeer). POS_SENT (NEG_SENT, NEU_SENT) is the firm-specific share of comments classified as positive (negative, neutral) sentiment within the different time windows. PASSIVEpeer indicates low posting activity on a firm's Facebook business page and equals 1 if the firm's number of postings is below the sample's daily median, and zero otherwise. REACTIVEpeer indicates new posting activity on a firm's Facebook page following a period of passivity and equals 1 if the firm's number of postings is above the sample's median after the firm's passivity. Our variable of interest is the three-way interaction term between FB user sentiment, PASSIVEpeer, and REACTIVEpeer. CAR is measured for the three days around the observation day [t-1; t; t+1]. See Appendix 2.2 for all variable definitions. Panels A to D represent the OLS regression results for a one-, three-, five- and seven-day period of posting passivity, respectively. Models I to XII report the results for positive sentiment (POS_SENT), negative sentiment (NEG_SENT) and neutral sentiment (NEU_SENT) for each of the four time windows [1-Day, 3-Day, 5-Day, 7-Day] a firm takes to reactivate its posting activity, respectively. Models are estimated using OLS regression with firm and year fixed effects (FE). Our results are validated with the slope difference test by Dawson and Richter (2006). In addition, we calculate the marginal effects of our sentiment measures and our two indicator variables for values of half a standard deviation (SD) below and above the mean and receive significant results ($p < 0.05$). All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at the client level are presented in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels based on two-tailed tests.*

2.6 Robustness tests

We conduct additional tests to validate our findings. First, one alternative explanation for the negative stock market impacts measured within periods of firms' social media passivity is that investors react timely to information disseminated by other news sources, i.e., traditional media. Specifically, firms may remain silent on social media when exposed to bad news in traditional media for a specific period. To exclude negative news periods on traditional media channels (online or paper-based) as a driver for negative investor sentiment, and thus, for decreasing stock prices, we replace our indicator for a firm's social media passivity (PASSIVE) with a newly developed indicator for above-average negative traditional media news in periods of the same length. Therefore, we employ our control variable for the penetration of traditional media channels by negative news, NEG_NEWS. In this fashion, we repeat our main regressions of Equation 1. We fail to find significant results, indicating no association between firms' social media passivity periods and periods of above-average bad news in traditional media. These findings support our main model's results.

Second, following Sul et al. (2014), we replace missing values for our sentiment measures with zero to validate our results further. This procedure assumes neutral sentiment for missing observations. Untabulated results show similar patterns of the results for all time windows. This supports our finding of neutral sentiment to be a non-influencing factor of a firm's stock returns.

Third, to control for potential reverse effects indicating that abnormal stock returns drive social media sentiment, we repeat all regressions from our main model that are displayed in Table 5 in a reversed fashion. We use the different time windows as a proxy for abnormal returns and measure our sentiment variables over a three-day period. We do not find any significant results, supporting our main findings.

Fourth, we conduct an in-time placebo test using placebo time windows for our sentiment variables to ensure that our regression results are not driven by our research design (e.g., Hahn and Shi 2017; Conley and Taber 2011; Bertrand, Duflo, and Mullainathan 2004). We run our main regression model shifting POS_SENT, NEG_SENT and NEU_SENT back and forth 10, 15 and 30 trading days, respectively, while keeping our dependent variable CAR constant. We do not find any significant results, indicating that assuming no treatment effects, there is no evidence of random or systematic errors due to a weak model design.

2.7 Conclusion

With rapidly enhancing technology, firms face a shift in their communication channels used for corporate disclosures and, as such, there is a shift in their information environment, that is hard to ignore. As investors increasingly rely on social media as a source for financial and other corporate news, firms that fail to participate in this conversation are likely to be noticed for their silence (Cade 2018). In this study, we investigate whether and how corporate social media passivity affects stock returns. We build on the wisdom of crowds and the herding theory to explain the formation of social media user sentiment and employ the theory of cognitive dissonance to account for the effects of social media passivity on user sentiment and trading decisions. Focusing on a group of firms with a homogenous social media performance, i.e., the 30 largest U.S. firms listed in the DJIA, we examine the strength, duration and neutralization times of the moderating effect of a firm's posting passivity on the relationship between its social media user sentiment and its future stock prices. Therefore, we apply two approaches to measure posting passivity. First, we compare the daily number of posts of each firm to the firm's peers, i.e., the median of our sample. Second, we consider the firm's historical posting activity as a reference. We employ a large-scale machine learning approach to measure a firm's daily social media sentiment in a broad sample of user comments on a firm's corporate FB page in the eight-year period 2009–2016.

We find that posting passivity reverses a positive effect of positive social media sentiment on stock returns, starting from a passivity period of five days. As this influence even exceeds the initial positive effect, FB users seem to penalize a firm's posting passivity after four days. If a firm is exposed to negative social media sentiment, posting passivity amplifies the negative effect on its stock returns, starting from a five-day period of passivity, with the negative effect more than doubled. These results hold true for both ways of measuring passivity, i.e., compared to the firm's peers and compared to the firm's historical posting activity, with the latter approach exhibiting higher magnitudes since firm-specific posting passivity is more obvious to investors. Moreover, the time it takes for firms to overcome this penalization effect increases with the duration of posting passivity.

Our findings contribute to both practice and research. First, they provide practical relevance to firms in rich information environments that actively use or consider using social media as a communication channel, both for financial and nonfinancial disclosures. Firms that are aware of the consequences of abandoning their social media platforms and, hence, their stakeholders, might be able to anticipate and strategically manage their reputation amongst investors. As such, firms that compete in a group with similar social media performance may eventually be put at risk, regardless of their overall investor relations efforts. Moreover, our study is relevant to regulators assessing the risks and benefits of using social media as a platform for corporate disclosures. Second, our findings add to the research on the impact of corporate social media use on the capital market, since they introduce the importance of continuity when using social media as a dissemination channel for corporate information.

Third, our study expands the definition of investor sentiment as a driver for stock prices by social media sentiment. Since investors increasingly rely on social media rather than on traditional news to make investment decisions, it seems essential to have an accurate and precise measurement of social media sentiment and its inclusion in the general dissemination strategy. This includes not only firm-level daily measurement but also sentiment splitting, as the effects of negative, positive, and neutral sentiment on the stock market are strongly diverse.

As with all studies, our study is limited in several ways and, as such, paves the way for future research. As we focus on large firms with homogenous social media performance, it is uncertain if our findings are applicable to small and medium size firms, or firms in less rich information environments. For example, investors in small firms may be satisfied with a lower posting frequency, since small firms tend to reach a smaller group of social media users and, thus, herding effects are mitigated. Moreover, in line with the wisdom of crowds theory, a smaller group of users is expected to process stock-relevant information less accurately.

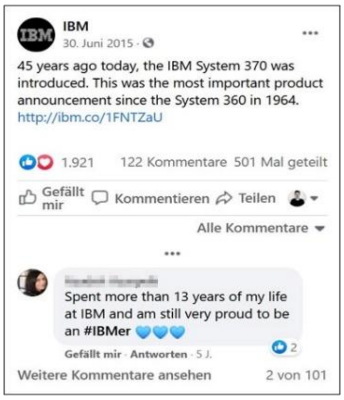
Additionally, it should be a matter of research whether the type of corporate information disclosed on social media triggers different investor perceptions and interacts differently with social media passivity.

This can help firms to properly assess the consequences of passive behavior on social media platforms. Additional research is needed to determine why firms choose to remain silent in certain situations—especially when research indicates that increasing their tweets on Twitter can mitigate investor uncertainty for firms with bad news (Miller and Skinner 2015) and proactive behavior on Twitter can efficiently manage crises, leading to weaker negative market reactions (Lee et al. 2015). Are firms unaware of the consequences of social media passivity or do they only lack appropriate measures for their received sentiment among social media users? Finally, as there is a spectrum of social media platforms employed by firms, i.e., Twitter, Instagram or YouTube, further studies will be necessary to validate or expand our findings.

Appendix 2.1

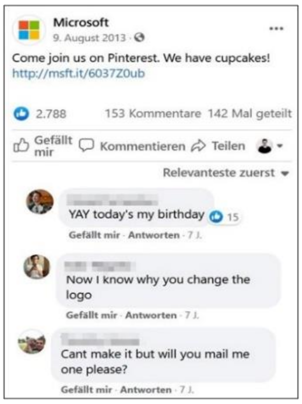
Examples: Sentiment classification of FB comments using support vector machine (SVM)

Panel A: Positive sentiment comments



Panel B: Negative sentiment comments

Panel C: Neutral sentiment comments



Notes: All examples of sentiment classification of FB comments using support vector machine (SVM) are retrieved from Facebook. Panel A (B) illustrates examples of comments classified as positive (negative) sentiment. Panel C illustrates examples of comments classified as neutral sentiment.

Appendix 2.2

Variable definitions

Variables	Definition	Data Source
Dependent Variable		
CAR	Cumulated Abnormal Returns as the sum of a firm's abnormal returns (AR). We measure CARs for the three days around the observation day [t-1; t; t+1]	Thomson Reuters EIKON
Variables of Interest		
POS_SENT	Firm-specific share of comments classified as positive sentiment within the different time windows.	FACEBOOK
NEG_SENT	Firm-specific share of comments classified as negative sentiment within the different time windows.	FACEBOOK
NEU_SENT	Firm-specific share of comments classified as neutral sentiment within the different time windows.	FACEBOOK
$\text{PASSIVE}_{\text{peer}}$	Indicates low posting activity on a firm's Facebook page. Equals 1 if the firm's number of postings is below the sample's daily median.	FACEBOOK
$\text{PASSIVE}_{\text{hist}}$	Indicates low posting activity on a firm's Facebook page. Equals 1 if the firm's number of postings is below the firm's daily average within the observation period.	FACEBOOK
$\text{REACTIVE}_{\text{peer}}$	Indicates new posting activity on a firm's Facebook page following a period of passivity. Equals 1 if the firm's number of postings is above the sample's median after the firm's passivity.	FACEBOOK
$\text{REACTIVE}_{\text{hist}}$	Indicates new posting activity on a firm's Facebook page following a period of passivity compared to the firm´s daily average within the observation period. Equals 1 if the firm's number of postings is above the firm's daily average within the observation period after the firm's passivity.	FACEBOOK
Control Variables		
AR	Firm's trading day abnormal returns adjusted by size and price-to-book matched characteristic portfolio returns calculated as $\boldsymbol{AR_t^i = R_t^i - R_t^{i,port}}$, where $\boldsymbol{R_t^i = ln(r_t^i + 1)}$ and $\boldsymbol{R_t^{i,port} = \frac{1}{n}\sum_{j=1}^{n} w_j\,(R_t^i)}$. Note that $\boldsymbol{r_t^i}$ is the daily total return. The sum of weights in each portfolio equals 1: $\boldsymbol{\sum_{j=1}^{n} w_j = 1}$. We calculate six size characteristic portfolios where inter-portfolio firms are ranked by price-to-book.	Thomson Reuters EIKON
NEG_NEWS	Natural logarithm of 1 plus the total number of negative news articles published in traditional media. We manually	FACTIVA

	collect the data for Dow Jones Newswire, The Wall Street Journal, USA Today, The Washington Post, The New York Times, The Los Angeles Times, Business Wire and Reuters News.	
FOLLOWING	Natural logarithm of 1 plus the number of analysts following a firm.	I/B/E/S
GOOGLE_SEARCH	Google Search Volume Index obtained from Google Trends that is normalized to values between 0 and 100 where each search query for a firm's name is divided by the total searches of the geography and time range it represents to compare relative popularity. GOOGLE_SEARCH = (# of queries for a firm's name)/(total Google search queries).	Google
INSTITUTIONAL	Percentage of shares held by institutional investors.	Thomson Reuters EIKON
LITIGATION	Indicates a firm's yearly exposure to a high litigation risk. Equals 1 if the firm is in the biotech (SIC codes 2833-2836 and 8731-8734), computer (3570-3577 and 7370-7374), electronics (3600-3674), or retail (5200-5961) industries, and sales growth, abnormal return and turnover are above the sample median and size and volatility are below the sample median.	Thomson Reuters EIKON
COMMENTS	Natural logarithm of 1 plus the total number of a firm's Facebook comments per trading day.	FACEBOOK
POSTS	Natural logarithm of 1 plus the total number of a firm's Facebook posts per trading day.	FACEBOOK
SHARES	Natural logarithm of 1 plus the total number of user shares of a firm's Facebook posts per trading day.	FACEBOOK

Notes: This table provides variable definitions for all variables used in our main regressions.

3 COVID-19 Pandemic and Capital Markets: The Role of Government Responses

3.1 Publication Details

Authors: Christian Beer, Janine Maniora and Christiane Pott

Abstract: This paper analyzes the moderation effect of government responses on the impact of the COVID-19 pandemic, proxied by the daily growth in COVID-19 cases and deaths, on the capital market, i.e., the S&P 500 firm´s daily returns. Using the Oxford COVID-19 Government Response Tracker (OxCGRT), we monitor 16 daily indicators for government actions across the fields of containment and closure, economic support, and health for 180 countries in the period from January 1, 2020 to March 15, 2021. We find that government responses mitigate the negative stock market impact and that investors´ sentiment is sensitive to a firm´s country-specific revenue exposure to COVID-19. Our findings indicate that the mitigation effect is stronger for firms that are highly exposed to COVID-19 on the sales side. In more detail, containment and closure policies and economic support mitigate negative stock market impacts, while health system policies support further declines. For firms with high revenue exposure to COVID-19, the mitigation effect is stronger for government economic support and health system initiatives. Containment and closure policies do not mitigate stock price declines due to growing COVID-19 case numbers. Our results hold even after estimating the spread of the pandemic with an epidemiological standard model, namely, the susceptible-infectious-recovered model (SIR).

Keywords: COVID-19, government policies, investor sentiment, capital market, sales revenue, behavioral finance

JEL-Codes: G11, G18, G41, I18, C23

Publication Status: Published. Journal of Business Economics, 93(1-2), 11-57, https://doi.org/10.1007/s11573-022-01103-x. Previous versions of this paper were presented at the 44th European Accounting Association (EAA) Annual Conference, May 2022.

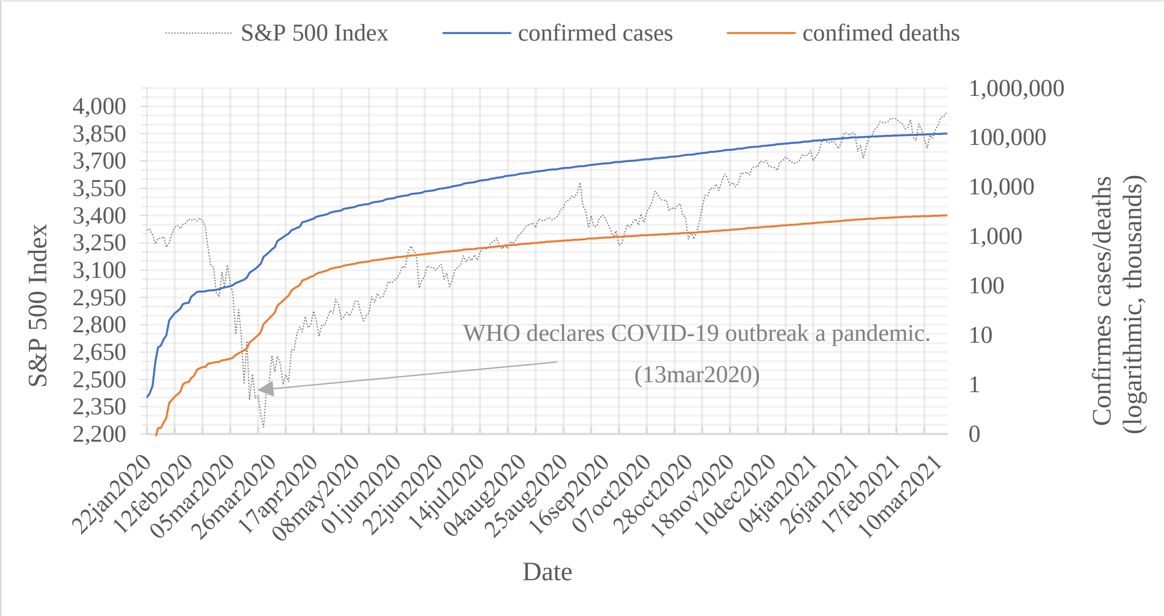
3.2 Introduction

The COVID-19 pandemic infected stock markets worldwide. Recent studies show negative investor reactions to be the strongest since the Spanish Flu of 1918 (Zhang et al. 2020). For instance, the S&P 500 index dropped by more than 30 percent compared to its all-time high on January 16, 2020. Several economic and social lockdowns caused unexpected, exogenous shocks that provoked a high level of uncertainty in the world´s capital markets (Baker et al. 2020; Zhang et al. 2020). A large amount of unfiltered negative news shaped investors' sentiment and expectations about the pandemic´s economic impact, reinforced market pessimism and triggered investor overreactions (Alexakis et al. 2021; Liu et al. 2021; Salisu and Vo 2020). In a recent study, Erdem (2020) reveals that the pandemic has a significant negative impact on a country's stock market index, with the growth in COVID-19 cases causing a three times larger decline in index prices than fatalities.

However, after the World Health Organization (WHO) pronounced COVID-19 a pandemic on March 13, 2020, it took only 26 days for the S&P 500 index to recover to its preannouncement value. Remarkably, another 158 days later, on August 18, 2020, the index again surpassed its all-time high from January 16, 2020. Figure 3.1 illustrates an overlay of the S&P 500 stock market index and the logarithmic growth of global confirmed COVID-19 cases and deaths for an observation period from January 1, 2020 to March 15, 2021.

What triggered investors to regain optimism rapidly, with the number of cases and deaths still rising? Recent studies on the capital market effects caused by the pandemic argue that government responses to contain the spread of the disease may play an important role in shaping investor sentiment during the pandemic (Alexakis et al. 2021; Hale et al. 2020; Salisu and Vo 2020). However, there is a lack of research on the relevance of government responses to COVID-19 for investor sentiment and capital markets. Only a few studies exist that, at an early stage, either discuss country-level macroeconomic impacts of government initiatives to contain the spread of the disease (e.g., Alexakis et al. 2021; Zaremba et al. 2020) or the impact of COVID-19 on investor sentiment (e.g., Jiang et al. 2021; Sun et al. 2020).

Figure 3.1: S&P 500 Index and globally confirmed COVID-19 cases and deaths (logarithmic)



Note: This figure shows the S&P 500 stock market index and logarithmic global confirmed COVID-19 cases and deaths for our observation period from January 1, 2020 to March 15, 2021. S&P 500 index data are derived from Thomson Reuters Datastream, and case and death data are obtained from the European Centre for Disease Prevention and Control (ECDC).

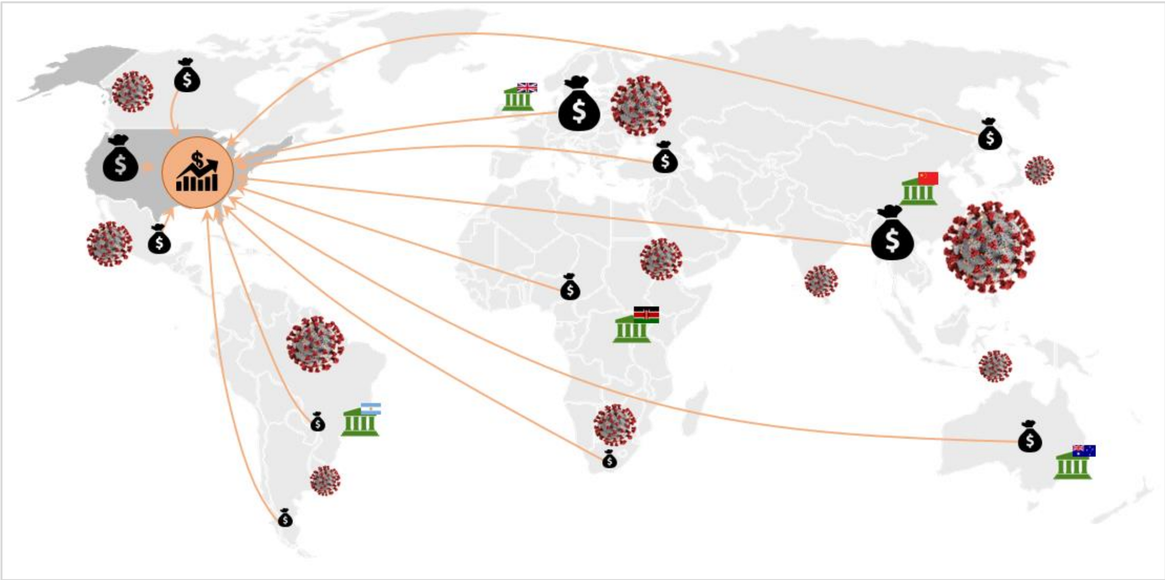
Research calls for studies that investigate the impact of government responses to COVID-19, differentiating government responses by their aim and scope to reveal diverse impacts on investor behavior and capital markets (e.g., Goodell 2020; Hale et al. 2020; Song et al. 2021). Undoubtedly, firms have a deep interest in how to react to a pandemic crisis depending on government policies, leading to the development of communication strategies by all groups of stakeholders. Existing research does not consider that investors of multinational companies (MNCs) are forced to incorporate the policies of multiple governments into their trading decisions. Research thus far does not consider that trust in governments impacts investor sentiment and trading behavior during the pandemic. As the literature provides evidence that external shocks (e.g., terrorist attacks) significantly reduce investors' trust (Lesmeister et al. 2018), government countermeasures to COVID-19 that reduce investors' uncertainty can be assumed to positively affect trust and mitigate stock price declines. In addition, recent studies show that firm-specific characteristics may serve as moderators of COVID-19-associated declines in stock prices. For example, Ding et al.

(2020) find that firms that are highly exposed to supply chain disruptions exhibit greater declines in returns. However, no study exists that analyzes associations with a firm´s sales side, i.e., sales revenues, by considering that investors can potentially evaluate the COVID-19 situation in other countries, where a large portion of a firm´s revenue is realized.

Our paper addresses this research gap. We argue that government responses influence investor sentiment, leading to diverse moderating effects on the association between the growth rates of COVID-19 cases, the number of deaths and stock market reactions. While restrictive policies may negatively influence investors' sentiment, increase pessimism, and trigger market overreactions, investors may also appreciate supportive efforts by governments, adjust their perceptions about market development, and, in consequence, positively adjust their investment decisions. Hence, governments may be able to actively reduce uncertainty, increase trust among investors and indirectly affect the stock market. We expect this two-sided effect to be an important driver of rapid stock market recovery during the pandemic.

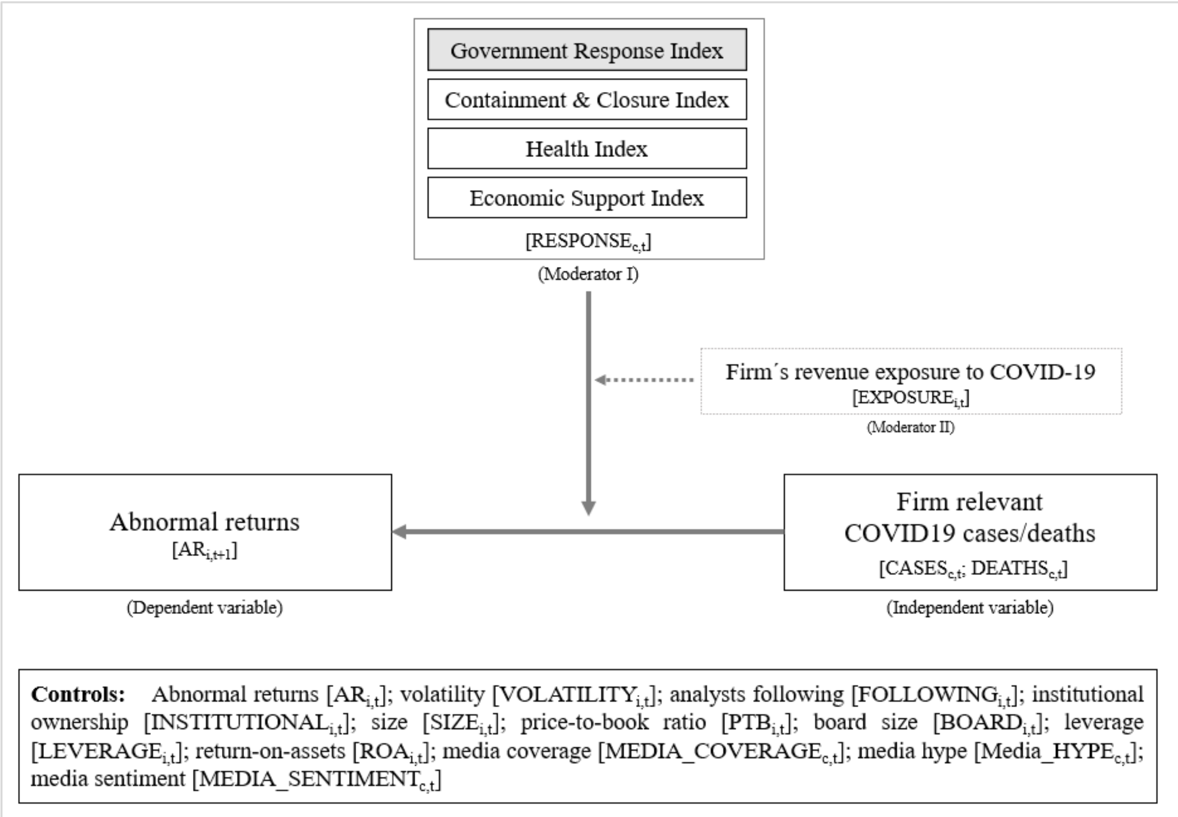
We build on the research of investor sentiment to explore the impact of the responses of 180 governments on the relationship between the stock prices of S&P 500 firms and the growth rates of COVID-19 cases and deaths in the period from January 1, 2020 to March 15, 2021. Specifically, we analyze 16 indicators covering three major fields of government policies, i.e., containment and closure, health system, and economic support, tracked by Oxford University´s Government Response Tracker (OxCGRT). We use country-specific revenues of each S&P 500 firm to solely assign government responses of firm-relevant countries to a firm and, in a second model, to reveal whether investors are aware of and react differently to a firm´s direct revenue exposure to COVID-19. Please see Figure 3.2 for an illustration of our sample structure and our research design.

Figure 3.2 Panel A: Illustration of our sample structure



Notes: This graphic illustrates the structure of our sample. We use the S&P 500 firm-specific daily abnormal stock returns to proxy for U.S. capital market effects. Each firm realizes sales revenues at different levels in various countries, symbolized by the money bag. At the same time, these countries are exposed to the COVID-19 pandemic with different severeness over time, symbolized by the virus pictogram. To contain the spread of the disease and to mitigate the economic and social impacts of the pandemic, the countries´ governments respond with country-specific actions and policies, symbolized by the government house pictogram.

Figure 3.2 Panel B: Research Design



Notes: This figure represents the design of our main regression model: COVID-19 cases and deaths of firm-relevant countries serve as the independent variables. Abnormal returns, measured as adjusted abnormal logarithmic returns using a market model, where expected returns are estimated with market betas using the firm's daily stock returns, and the S&P 500 index returns of the respective period, is the dependent variable. We employ two moderators to test for interactions with our COVID-19 proxies. First, a set of three government response indices, calculated from 16 indicators covering three major fields of government policies, i.e., containment and closure, health system, and economic support, tracked by the Oxford University´s Government Response Tracker (OxCGRT), including a summarizing index to reflect the entirety of government responses. Second, a firm´s specific revenue exposure to COVID-19 was calculated by weighting the country-specific sales revenues of our sample firms with the country´s growth rates of COVID-19 cases and deaths per million.

Results reveal that aggregated government responses mitigate the decline of stock returns due to both rising COVID-19 cases and deaths. Governments´ actions in the fields of containment and closure as well as economic support are most likely appreciated by investors and mitigate negative stock market impacts caused by the pandemic. In contrast, government actions concerning a country´s health system provoke further declines in abnormal stock returns. One reason could be the absence of initiatives that support health systems, e.g., widespread testing or vaccination campaigns, in the initial period of the pandemic. In general, health system initiatives are delayed compared to other government responses, causing uncertainty among investors. The mitigating effect of government responses in the field of economic support is stronger for firms that are highly exposed to COVID-19 on the sales side. We fail to find such effect for containment and closure policies, indicating that they are not strong enough for investors to adjust their pessimistic views on market development. Our results are relevant for firms in anticipating and strategically managing investor relations and in actively demanding government interventions. They are further valuable for governments in discussing the economic costs and benefits of their responses to pandemics. Moreover, our study contributes and expands the knowledge about investor sentiment during crisis situations caused by external shocks.

3.3 Literature Review and Research Questions

Investor sentiment and capital markets

The literature on behavioral finance has extensively explored whether investor sentiment affects trading decisions, leads to irrational trading behavior, and affects stock prices (e.g., Baker and Wurgler 2006; Beer and Zouaoui 2012; Chau et al. 2016; Cormier et al. 2010; Fang and Peress 2009; He et al. 2020; Hong and Stein 2007; Hong and Stein 1999; Kaniel et al. 2008; Long et al. 1990; Palomino 1996; Shleifer and Vishny 1997). Bollen and Mao (2011a) find that investors' trading behavior is directly shaped by their perceptions about future market development. Anxiety increases investors' risk avoidance and contributes to pessimism (Baker and Wurgler 2006; Cen et al. 2013).

One relevant driver of investor perceptions and expectations is news. Tetlock (2007) shows that news media pessimism predicts downward pressure on market prices, even leading to a revision of fundamentals. Subsequent studies find that bad news leads to more intense or even panic-driven, long-term stock market effects (Cohen et al. 2018; Jung et al. 2018; Miller and Skinner 2015). A subordinate literature stream covers the formation and consequences of investor overreactions. In a fundamental study, DeBondt and Thaler (1985) investigate whether, and following which rules, the stock market overreacts. They present experimental evidence that in probability revision problems, people show a tendency to overreact, i.e., they overweight recent information and underweight base rate data. Barberis et al. (1998) link investor overreactions to news. They analyze the impact of good and bad market-relevant news announcements as a moderator of investor overreaction and stock return developments. Results show that investors overreact to consistent patterns of good (bad) news with a correlation to the length of good (bad) news series. Michayluk and Neuhauser (2006) analyze the role of investor overreaction during the market decline following the 1997 Asian financial crisis. They conclude that overreaction is sensitive to news announcements and is traceable for one week after the announcement. On a different note, Gennailoi et al. (2015) argue that a single piece of bad news in a series of good news items will not lead to a change in the underlying beliefs of investors regarding certain stocks. Nevertheless, a continuous series of bad news results in investor overreaction because previously ignored bad news is remembered, 'leading to a sharp rise in the perceived probability of a crisis and a collapse of prices' (Gennailoi et al. 2015, p. 312).

Another influencing factor on investor sentiment is trust. Georgarakos and Pasini (2011) find an association between trust in financial markets and investors’ trading behavior. Based on a portfolio model using survey data, they show that in countries where investors exhibit a high level of trust toward the capital market, the stockholding share is significantly higher than in low-trust countries. Lesmeister et al. (2018) analyze whether shareholders extend or reduce their monitoring activity (e.g., by shareholder votes) relative to the general trust that they experience. The study reveals that trust reduces the amount of shareholder monitoring activity. Moreover, when exposed to external shocks, such as terrorist attacks, investors’ trust decreases by an increase in announced fatalities.

Investor sentiment during epidemics/pandemics

As financial crises caused by epidemics or pandemics are not without precedent, few studies have taken the occasion of previous health crises to expand the knowledge of their power to impact investor sentiment. Funck and Gutierrez (2018) examine the impact of Ebola headline news on media-highlighted stocks. They employ the *VIX-Investor Fear Gauge* (VIX), introduced by Whaley (2000), to proxy for investor pessimism during Ebola outbreak announcements. They reveal that stock prices tend to reverse themselves within one day after the announcement, supporting the traditional theory of investor overreaction. Avian influenza (bird flu), initially reported in China in March 2013, caused a loss in the agriculture sector by $6.5 billion due to changes in prices, consumer confidence and trade volumes. Jiang et al. (2017) explored the impact of daily avian influenza case announcements on stock prices. They find peaks in investors’ overreacting behavior within the initial outbreak announcements; that is, investors seem to act more reasonably in time when the shock of the first outbreak news has been overcome.

Ichev and Marinč (2018) focus on the 2014–2016 Ebola outbreak. They analyze the effect of mass media news announcements about Ebola outbreak events on firms' stock returns. They find that investors act irrationally to the news on the Ebola outbreak and that Ebola outbreak events unequally affect investors' sentiment about stock returns, depending on the distance of the outbreak event from the markets. Negative effects on financial markets are stronger for firms that operate in countries with a larger Ebola exposure. They conclude that a firm´s geographic proximity to the Ebola outbreak event increases the impact on its stock returns.

In a recent study, Engelhardt et al. (2020) find that COVID-19-induced stock market declines in 64 countries are mainly associated with greater news attention and less with rational expectations. Following this research, we expect the growth rates of COVID-19 cases and deaths in firm revenue-relevant countries to depress investor sentiment by provoking panic and pessimism, resulting in temporary market overreactions and leading to a decline in stock returns during the pandemic.

Government responses to the COVID-19 pandemic and investor sentiment

With rising COVID-19 cases and deaths, several governments worldwide took action to mitigate the repercussions of the disease and introduced diverse sets of countermeasures, i.e., government responses. In addition to restrictive policies to contain the spread of the disease (e.g., travel restrictions, stay-at-home requirements, school closings, public transport closings), stimulus packages were implemented to mitigate the economic impact of the pandemic (e.g., income support, debt relief, fiscal measures). Moreover, proactive measures were set in motion to reduce infection rates (e.g., testing policies, vaccination policies, contract tracing) (Hale et al. 2020). Following the literature on investor sentiment, we argue that government responses to COVID-19 can reinforce or mitigate the negative impact of the COVID-19 pandemic on stock prices. Governments may reduce uncertainty among investors, regain investors´ trust and lead to a less severe decline, or even rise, of firms´ stock returns, depending on the aim and scope of the policy. Moreover, we expect investors to rate government responses differently depending on a firm´s exposure to COVID-19; this is how severely those firm-relevant countries are affected, which directly contribute to the firm´s revenues.

3.4 Data and Research Design

3.4.1 COVID-19 data

We obtain daily data on worldwide confirmed COVID-19 cases and deaths per country from January 1, 2020 to March 15, 2021 from the *European Centre for Disease Prevention and Control (ECDC)*. We calculate the daily growth rates of both cases and deaths in each country, relative to a country´s population, by dividing the number of daily cases and deaths per million in country *i* on day *t* by the same measure of the previous day *t-1*. We receive a subsample of 180 countries and 563 observation days per country. Our sample is unbalanced since, for some sample countries, no cases or deaths were reported until April 2020.

3.4.2 Capital market data

To measure firm-level stock market reactions to the COVID-19 pandemic, we obtain daily stock prices for 511 firms that make up the S&P 500 index during our observation period from January 1, 2020 to March 15, 2021. To solely assign COVID-19 cases and deaths and government responses of firm-relevant countries to a firm, we obtain country-specific sales revenues [$REVENUE_{i,c,t}$] for the compounding S&P 500 firms for 2019 from the *FactSet Geographic Revenue (GeoRev)* Database. We assign all countries to a firm that contributed to the firm´s revenues, leading to a combination of multiple countries for each firm per observation day. We only include values with a certainty score of 70 or above, as provided by *GeoRev*. The certainty score is based on source metadata and ranges from 1 (low certainty) to 80 (declared value). This proceeding enables us to isolate information that is assumed to be of decision-relevant significance to each firm´s investors. See Appendix 1 for a list of countries included and the number of firms that realize revenues in the respective country.

3.4.3 Government response data

We employ data from the OxCGRT, published by Hale et al. (2020), to measure country-specific government responses to the pandemic. Our dataset covers 16 individual ordinal scaled indicators that represent the strictness of various government policies in response to the COVID-19 pandemic. It should be noted that these values do not reflect the effectiveness of each policy. All indicators can be classified into three groups, representing the scope of the policy, i.e., containment and closure policies, health system policies, and economic policies. We include the following indicators:

Containment and closure policies

School closings; workplace closings; cancelations of public events; restrictions on gatherings; closing of public transport; stay-at-home requirements; restrictions on international movement; international travel controls

Health system policies

Public information campaigns; testing policy; contact tracing; facial covering policy; vaccination policy; protection of elderly people

Economic policies

Income support; debt and contract relief

Please see Appendix 2 for a full list of indicators, including detailed descriptions and scale coding. To reflect the extent of each government´s efforts, we calculate an index for each of the three policy groups.[16] Since all indicators are ordinally scaled and ranked with different values set as maximums, we calculate subindices to normalize each indicator to an equally spaced scale between 0 and 100. The three indices, i.e., containment and closure index, health system index, and economic support index, are then calculated as simple averages of the normalized individual subindices. Moreover, we aggregate all three indices to create a summarized government response index. We merge our government response data with the firm-country dataset, including growth rates in the number of cases and deaths. Our final sample consists of 10,060,911 daily firm-country-specific observations.

3.5 Empirical Model

To test whether government responses to the COVID-19 pandemic moderate the impact of confirmed and announced COVID-19 cases and deaths on firms' daily stock returns, we

[16] In the original dataset, Hale et al. (2020) present four indices to give an overall impression of government activity. However, these indices cover a mix of indicators from all three policy groups. To accurately reflect government responses of each policy group, we calculate our own indices, solely including indicators of the assigned group of policies.

* We also control for country-fixed (Country FE) effects as part of our robustness tests. Please see Section 5.

estimate the following regression model using firm- (Firm FE) and day-fixed (Day FE) effects*:

$$\mathbf{AR_{i,t+1} = \beta_0 + \beta_1 * COVID\text{-}19_{c,t} + \beta_2 * RESPONSE_{c,t} + \beta_3 * COVID\text{-}19_{c,t} \times RESPONSE_{c,t} + \sum_{j=1}^{14} \beta\_co_j * Controls_{i,c,t,j} + Firm\ FE_i + Day\ FE_t + \varepsilon_{i,t}} \quad (3)$$

where *i*, *c*, and *t* index firm, country, and day, respectively.

Our dependent variable [$AR_{i,t+1}$] is measured as adjusted abnormal logarithmic returns using a single-index market model, where expected returns are estimated with market betas using the firm's daily stock returns and the S&P 500 index returns of the respective period (e.g., Brown and Barry 1984; Dai et al. 2020; Jain 1986; Sharpe 1963). Specifically, we define abnormal returns as $\boldsymbol{AR_t^i = R_t^i - E(R_t^i)}$, where $\boldsymbol{R_t^i}$ represents the daily return for firm *i* on day *t*. We estimate the firm´s expected return as $\boldsymbol{E(R_t^i) = \alpha_i + b_i * E(R_t^{market})}$, with $\boldsymbol{R_t^{market} = (P_t^{market} - P_{t-1}^{market})/P_{t-1}^{market}}$, where $\boldsymbol{P_t^{market}}$ represents the S&P 500 index closing price on day *t*. [17] Following prior research on the stock market impact of infectious diseases, our model parameters are estimated over a 90-trading-day estimation period, starting one day prior to day *t* to prevent unusual effects on the measurement day from interfering the estimation (e.g., Liu et al. 2020; Wang et al. 2012).

COVID-$19_{c,t}$ represents either the growth rate of the announced cumulative number of confirmed COVID-19-positive cases [$CASES_{c,t}$] or deaths [$DEATHS_{c,t}$] associated with or caused by the disease per million in country *c* for day *t*. $RESPONSE_{c,t}$ corresponds to each of our four daily government response indices, i.e., containment and closure index [$CONTAINMENT\_CLOSURE_{c,t}$], health system index [$HEALTH\_SYSTEM_{c,t}$], economic support index [$ECON\_SUPPORT_{c,t}$], and the summarized government response index [$GOV\_RESPONSE_{c,t}$]. We use a set of control variables based on prior literature. We control

[17] Since the COVID-19 pandemic most likely causes widespread systematic effects across firms and sectors worldwide, it is imperative to employ alternative and neutral benchmarks for calculating abnormal returns. Thus, we repeat our analysis using a portfolio-based approach to calculate abnormal returns based on firm-specific risk. In addition, we recalculate our models using the daily average market return of the entire US market instead of focusing the S&P 500. Both analyses are presented in section five (Robustness Tests).

for abnormal returns one day prior to the measurement day by using abnormal returns [$AR_{i,t}$] in autoregression to consider stock return autocorrelation (e.g., Kraft and Kraft 1977; Smirlock and Starks 1988). Zaremba et al. (2020) and Ali et al. (2020) reveal a significant impact of the COVID-19 pandemic on market volatility. Hence, we include a firm´s annualized volatility of logarithmic stock returns during our observation period [$VOLATILITY_{i,t}$]. We control for the number of analysts following a firm´s share [$FOLLOWING_{i,t}$] as well as for the percentage of institutional holdings [$INSTITUTIONAL_{i,t}$], with both variables to be measured annually (e.g., Bartov et al. 2018; Chen et al. 2013; Hong et al. 2000). A broad number of studies investigate the relationship between firm fundamentals and stock market returns. We follow these findings by including firm size as proxied annually by the logarithm of a firm´s total assets [$SIZE_{i,t}$] and the price-to-book ratio as a firm´s daily market price per share divided by the share´s book value [$PTB_{i,t}$] (e.g., Fama and Franch 1993; Griffin and Lemmon 2002; Pontiff and Schall 1998). Moreover, corporate governance research finds that the number of a firm´s board members shapes board integrity and effectiveness and, thus, reinforced by the perception of investors, affects returns (Cheng 2008; González et al. 2019). Hence, we include the quarterly board size [$BOARD_{i,t}$] in our set of controls. Davison (2020, p. 2) finds that 'the stocks returns of firms who are relatively unable to transition their business to comply with social distancing are much more responsive to changes in their level of leverage going into the pandemic'. We, therefore, process a firm´s leverage change during our observation period as the yearly differences in the ratio of a firm´s book value debt and total assets [$LEVERAGE_{i,t}$]. Hu and Zhang (2021) show that firm performance deteriorates during the COVID-19 pandemic. However, the effect is smaller for firms in countries with better health systems, more advanced financial systems, and better institutions. We address these findings by controlling for the quarterly change in a firm´s return-on-assets [$ROA_{i,t}$], calculated as operating income before depreciation over total assets. Several studies discuss a firm´s economic, social, and governmental scores (ESG scores) to indicate the resilience of stock prices during the COVID-19 pandemic. However, the results of preliminary studies are controversial. Albuquerque et al. (2020) find that stocks with higher ESG scores have significantly higher returns, lower return volatility, and higher operating profit margins during the first quarter of 2020. Broadstock et al. (2021) add that ESG performance mitigates financial risk during a financial crisis and that high-ESG portfolios generally outperform low-ESG portfolios. In contrast, Demers et al. (2021) conclude that higher ESG scores do not immunize stocks. We control for ESG scores [$ESG_{i,t}$] using the most prevalent *Refinitiv* ESG *SCORE*[18] that weekly measures a company's relative ESG performance, commitment and effectiveness across 10 main themes, including emissions, environmental product innovation and human rights (Refinitiv, 2020a). Since the discussed literature on investor sentiment assigns an important role in affecting investor sentiment to news media, we control for three variables covering the spread, perception, and sentiment of COVID-19 news in each country. Data were obtained from the *RavenPack Coronavirus Media Monitor*. $MEDIA\_COVERAGE_{c,t}$ calculates the daily percentage of all news agencies in country c on day t covering the topic of COVID-19. The index is computed as the daily number of distinct news agencies that mention COVID-19, divided by the total available number of news agencies in the country. $MEDIA\_HYPE_{c,t}$ measures the percentage of news that is currently reporting about COVID-19 in country c on day t, regardless the originating news agency. The index is computed as the daily number of reports that mention COVID-19, divided by the total daily number of reports. $MEDIA\_SENTIMENT_{c,t}$ measures the level of sentiment that news reports express towards a firm that is mentioned in the report alongside COVID-19. Specifically, it reflects the daily average of the difference between the number of positive and negative news reports. *RavenPack* determines positive or negative sentiment by 'systematically matching stories usually categorized by financial experts as having a positive or negative financial or economic impact. The algorithm produces a score for more than 6,900 categories of business, economic, and geopolitical events, ranging from earnings announcements to natural disasters.' (Hafez et al. 2020). The index ranges between -100 and 100, where a value of 100 is the most positive sentiment, -100 is the most negative, and 0 is neutral. All variables are defined in Appendix 3.

3.6 Empirical Results

3.6.1 Summary statistics

Table 2.1 reports descriptive statistics for all variables in our main regression model specifications. All variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The mean value of firm-specific abnormal returns is 0.001 [$AR_{i,t+1}$].

[18] "ESG scores by Refinitiv have been used (or referenced) in more than 1,200 academic articles over the past 15 years. Moreover, Refinitiv ESG data are used by major asset managers, such as BlackRock, to manage ESG investment risks. Refinitiv ESG data are also referenced in an ESG white paper featured at the World Economic Forum in 2019 (WEF, 2019), and analyzed as one of the three key ratings providers in a recent OECD report." (Boffo and Patalano 2020).

The mean annualized volatility of stock returns is 31.336 [$VOLATILITY_{i,t}$], which is remarkable since the S&P 500's annualized average volatility from 1926 through 2017 is 15.2.[19] The mean share of revenues that a firm derives from a country is 1.126% [$REVENUE_{i,c,t}$], with a maximum share of 53.175%. This maximum coincides with the average revenue share that S&P 500 firms realize in the United States, as expected. As the median value is 0.083 and the 75th percentile shows a value of 0.301, the highest revenue firms are allocated to a small number of countries. On average, a firm is followed by 22 analysts [$FOLLOWING_{i,t}$], and the mean share of institutional owners [$INSTITUTIONAL_{i,t}$] is 82.829%. Firm size [$SIZE_{i,t}$], price-to-book-ratio [$PTB_{i,t}$], and the level of leverage [$LEVERAGE_{i,t}$] show mean values of 223.730 bn, 5.730, and -0.973, respectively. A firm´s board comprises approximately 11 members. Unsurprisingly, concerning firm performance, the average return on assets is negative at -1,656%. *Thomson Reuters Refinitiv* calculates a mean ESG score [$ESG_{i,t}$] of 63.582 for our sample firms. Turning to country-specific data, on average, a country is exposed to a daily growth of 5.926% in COVID-19 cases per million people [$CASES_{i,t}$] and a daily growth in COVID-19-related deaths per million people of 0.129% [$DEATHS_{c,t}$]. We calculate our index for a country´s containment and closure policies [$CONTAINMENT\_CLOSURE_{c,t}$] to average 49.616. Values for our index covering a country´s efforts to support the health system [$HEALTH\_SYSTEM_{c,t}$] as well as the economy [$ECON\_SUPPORT_{c,t}$] rank closely at 54.449 and 43.965, respectively. Our summarized measure for a government´s effort in all fields [$GOV\_RESPONSE_{c,t}$] exhibits a mean value of 54.940. Our controls for the spread, perception, and sentiment of COVID-19 news in each country reveal the following descriptive insights: On average, 55.511% of all news agencies in a country cover the topic of COVID-19. The percentage of news that reports on COVID-19 each day in a country is 46.118. The mean level of sentiment toward a country mentioned in the news alongside COVID-19 is -5.930, with an overall sample maximum of 50.950 of 100 index points and a minimum of -97.210. The median remains negative at -2.460.

[19] Source: *RefinitivDatastream*

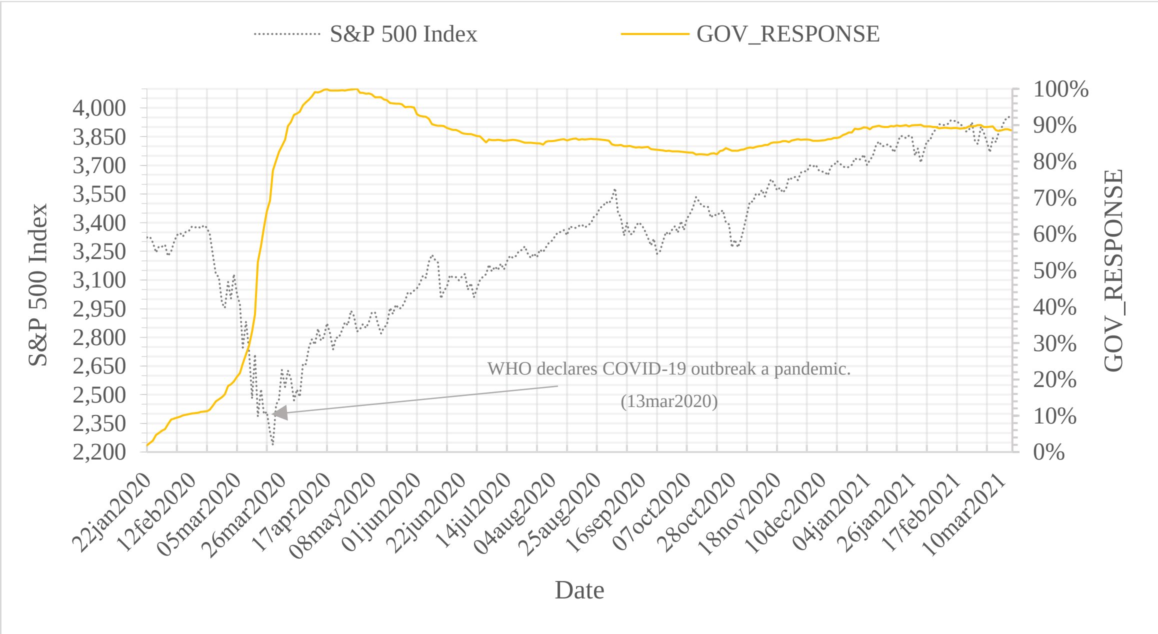
Table 3.1: Descriptive statistics

Variable	Mean	Std.	Min.	25%	Median	75%	Max.	N
Firm characteristics:								
AR	0.001	2.107	-6.606	-1.056	-0.021	1.019	7.190	155,855
VOLATILITY	31.336	10.380	15.948	24.014	29.405	35.321	66.822	155,855
FOLLOWING	21.604	8.008	5.000	16.000	21.000	26.000	46.000	155,855
INSTITUTIONAL	82.829	12.392	49.054	75.374	84.711	92.795	99.690	155,855
SIZE	232.730	370.861	12.651	47.178	110.660	236.010	2,455.100	155,855
PTB	5.730	32.942	-194.226	1.671	3.858	7.752	176.193	155,855
BOARD	10.974	2.027	6.000	10.000	11.000	12.000	17.000	155,855
LEVERAGE	-0.973	6.118	-23.400	-3.000	0.000	2.230	14.370	155,855
ROA	-1.656	4.203	-19.450	-2.630	-0.850	0.300	7.420	155,855
ESG	63.582	14.877	22.824	53.065	66.259	74.310	89.299	155,855
REVENUE	1.126	6.035	0.010	0.027	0.083	0.301	53.175	155,855
Country characteristics:								
CASES	5.926	31.701	-75.000	0.336	1.073	3.185	2200.265	54,900
DEATHS	0.129	1.458	-3.704	0.000	0.112	0.045	113.953	54,900
CONTAINMENT_ CLOSURE	49.616	27.904	0.000	31.250	54.688	71.875	100.000	54,900
HEALTH_SYSTEM	54.449	23.873	0.000	44.643	59.524	71.429	100.000	54,900
ECON_SUPPORT	43.965	33.230	0.000	0.000	50.000	75.000	100.000	54,900
GOV_RESPONSE	54.940	25.567	0.000	44.058	62.609	73.333	100.000	54,900
MEDIA_COVERAGE	55.511	21.086	0.060	43.270	59.500	71.250	100.000	54,900
MEDIA_HYPE	46.188	20.551	0.000	33.550	46.910	60.310	100.000	54,900
MEDIA_SENTIMENT	-5.930	12.767	-97.210	-10.060	-2.460	0.440	50.950	54,900
EXPOSURE	16.098	21.669	0.000	0.000	5.003	26.849	100.000	54,900
Observations in the firm-country-day-Matrix: 10,060,911								

Notes: This table provides the descriptive statistics for all variables. All variables are winsorized at the 1st and 99th percentiles.

Figure 3.3 shows the S&P 500 stock market index and the intensity of the global government response index [$GOV\_RESPONSE_{c,t}$] to COVID-19 for our observation period from January 1, 2020 to March 15, 2021. The intensity of global government responses is calculated by accumulating all 16 policy indicators per day over all 180 countries. The scale is normalized on a range of 0 to 100, where 100 represents the maximum intensity for the observation period. From March 5, 2020 on, worldwide initiatives to contain the spread of the pandemic are increasingly put in place. Hence, the global government response index grows exponentially. The growth accelerates from March 13, 2020, when the WHO declares the COVID-19 outbreak to officially be a pandemic. At the same time, the S&P 500 stock market index experiences a decrease that seemingly mirrors the government response´ s development. After a peak on April 17, 2020, the response index values diminish throughout the summer months, starting from approximately the date when the S&P 500 index recovers to its pandemic pre-announcement value. Towards winter, global government responses increase again slightly despite a continuously bullish stock market.

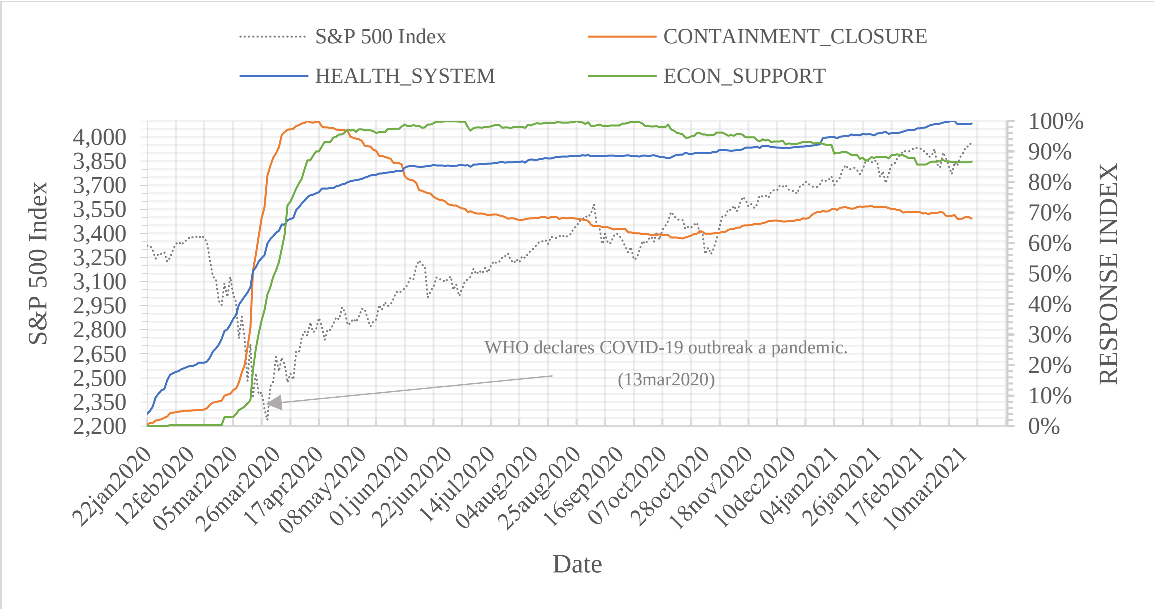
Figure 3.3: S&P 500 Index and global government response index



Note: This figure shows the S&P 500 stock market index and the intensity of accumulated global government responses to COVID-19 for our observation period from January 1, 2020 to March 15, 2021. S&P 500 index data are derived from Refinitiv Datastream. Data for the calculation of the global government response intensity are provided by the Oxford COVID-19 Government Response Tracker (OxCGRT) database. The intensity of global government responses is calculated by accumulating all 16 policy indicators per day over all 180 countries. The scale is normalized on a range of 0 to 100, where 100 represents the maximum intensity for the observation period.

Figure 3.4 shows the S&P 500 stock market index and the intensity of accumulated global government responses to COVID-19 for our observation period, split for policies in the fields of containment and closure [$CONTAINMENT\_CLOSURE_{c,t}$], health system [$HEALTH\_SYSTEM_{c,t}$], and economic support [$ECON\_SUPPORT_{c,t}$]. As before, the scale is normalized on a range of 0 to 100, where 100 represents the maximum intensity for the observation period. All three indices follow the path of the accumulated, global government response index, as illustrated in Figure 3.3. However, health system initiatives are implemented later compared to containment and closure policies or economic support. Containment and closure policies experience the strongest decline, with health system initiatives still increasing. In the course of the bullish stock market, economic support and containment and closure policies are reduced, while health system support is still being extended.

Figure 3.4: S&P 500 Index and global government responses by scope: containment and closure index, health system index and economic support index



Note: This figure shows the S&P 500 stock market index and the intensity of global government responses in the fields of containment and closure, health systems, and economic support for COVID-19 for our observation period from January 1, 2020 to March 15, 2021. S&P 500 index data are derived from Thomson Reuters Datastream. Data for the calculation of the global government response intensity are provided by the Oxford COVID-19 Government Response Tracker (OxCGRT) database. The intensity of each global government response field is calculated by accumulating all field-specific policy indicators per day over all 180 countries. The scale is normalized on a range of 0 to 100, where 100 represents the maximum intensity for the observation period.

Table 2.2 presents the Pearson-Spearman correlations. Both $CASES_{c,t}$ and $DEATHS_{c,t}$ are significantly negatively correlated with $AR_{i,t+1}$ (Pearson -0.042; Spearman -0.029 and Pearson -0,027; Spearman -0,022). This is a first indicator of the negative impact that rising COVID-19 cases and deaths cause on stock prices. $GOV\_RESPONSE_{c,t}$ shows a significant and positive correlation with AR (Pearson 0.023; Spearman 0.019), as $CONTAINMENT\_CLOSURE_{c,t}$ does (Pearson 0.064; Spearman 0.055). In contrast, correlation coefficients for the remaining two indices, $HEALTH\_SYSTEM_{c,t}$ and $ECON\_SUPPORT_{c,t}$, are significantly negative regarding $AR_{i,t+1}$ (Pearson -0.032; Spearman -0.041 and Pearson -0.029; Spearman -0.018). These findings imply that a split investigation of government responses is imperative since different government policies may provoke different market reactions. All four government response indices are significantly and positively correlated to both $CASES_{c,t}$ and $DEATHS_{c,t}$, exhibiting high magnitudes (e.g., $COV\_RESPONSE_{c,t}$ is correlated to $CASES_{c,t}$ with Pearson 0.0552; Spearman 0.427). This illustrates the sensitivity of government interventions worldwide to rising COVID-19 cases and deaths. Turning to our controls, we find interesting values for our news media measures. As expected, both $MEDIA\_COVERAGE_{c,t}$ and $MEDIA\_HYPE_{c,t}$ are positively correlated with $CASES_{c,t}$ and $DEATHS_{c,t}$ (e.g., MEDIA $COVEERAGE_{c,t}$ and $CASES_{c,t}$ Pearson 0.192; Spearman 0.140). However, $MEDIA\_SENTIMENT_{c,t}$ is negatively correlated with COVID-19 proxies ($CASES_{c,t}$: Pearson -0.078; Spearman -0.110, $DEATHS_{c,t}$ Pearson -0.124; Spearman -0.123). This leads to the interpretation that the amount of news that mentions COVID-19 and specific countries increases as COVID-19 cases and deaths grow. At the same time, the sentiment expressed in the news media toward countries becomes negative as COVID-19 numbers grow. Overall, the absence of high correlations among our variables suggests that there are no multicollinearity concerns.

Table 3.2: Pearson-Spearman correlations

VARIABLE	TOTAL_ RETURN	AR	VOLA-TILITY	FOLLOW ING	INSTI-TUTIO-NAL	SIZE	PTB	BOARD	LEVE-RAGE	ROA	ESG	REVE-NUE	CASES	DEATHS	CONAIN-MENT_ CLOSURE	HEALTH_ SYS-TEM	ECON_ SUP-PORT	GOV_ RES-PONSE	MEDIA_ COVER-AGE	MEDIA_ HYPE	MEDIA_ SENTI-MENT
AR	0.594*		0.164*	0.018*	0.002*	-0.056*	-0.037*	-0.031*	-0.051*	-0.009*	-0.038*	-0.006*	-0.029*	-0.022*	0.055*	-0.041*	-0.018*	0.019*	0.099*	0.091*	-0.037*
VOLATILITY	0.222*	0.244*		0.114*	0.044*	-0.175*	-0.223*	-0.080*	-0.255*	-0.204*	-0.162*	-0.027*	0.022*	0.021*	0.016*	0.018*	0.018*	0.020*	0.012*	0.008*	-0.008*
FOLLOWING	0.018*	0.033*	0.146*		-0.341*	0.431*	0.100*	0.087*	-0.112*	-0.070*	0.123*	-0.004*	-0.009*	-0.009*	0.001*	-0.004*	-0.005*	-0.002*	0.000	0.004*	0.002*
INSTITUTIONAL	-0.031*	-0.034*	-0.099*	-0.284*		-0.521*	0.007*	-0.251*	0.107*	0.059*	-0.339*	0.006*	0.006*	0.006*	-0.003*	0.001*	0.006*	0.000	0.002*	0.000	-0.006*
SIZE	-0.022*	-0.030*	-0.089*	0.366*	-0.460*		-0.098*	0.485*	0.009*	0.051*	0.471*	-0.023*	-0.003*	-0.002*	0.000*	0.000	-0.004*	-0.001*	-0.004*	-0.003*	0.003*
PTB	-0.013*	-0.019*	-0.039*	0.042*	-0.013*	0.009*		-0.109*	0.111*	0.173*	-0.049*	0.014*	0.023*	0.016*	-0.034*	0.022*	-0.006*	-0.017*	-0.055*	-0.048*	0.016*
BOARD	-0.011*	-0.029*	-0.067*	0.066*	-0.199*	0.172*	-0.014*		-0.048*	-0.051*	0.297*	-0.005*	0.001*	0.000	-0.001*	0.003*	0.001	0.000*	-0.004*	-0.004*	0.002*
LEVERAGE	-0.096*	-0.105*	-0.382*	-0.084*	0.201*	0.015*	0.039*	-0.086*		0.287*	-0.052*	-0.015*	0.003*	0.005*	0.000	-0.001*	0.002*	0.001*	0.002*	0.000	-0.007*
ROA	-0.105*	-0.094*	-0.387*	-0.066*	0.197*	0.099*	0.062*	-0.066*	0.473*		0.041*	-0.007*	-0.009*	-0.007*	-0.007*	-0.012*	-0.009*	-0.009*	0.000	-0.001*	-0.003*
ESG	-0.024*	-0.035*	-0.124*	0.093*	-0.295*	0.317*	0.007*	0.261*	-0.026*	0.072*		0.011*	-0.018*	-0.019*	-0.004*	-0.011*	-0.017*	-0.011*	-0.009*	-0.003*	0.014*
REVENUE	0.002*	0.002*	0.002*	-0.016*	0.005*	0.001*	-0.004*	0.001*	0.002*	0.000	-0.023*		0.175*	0.228*	0.076*	0.205*	0.194*	0.177*	0.175*	0.028*	-0.278*
CASES	0.043*	-0.042*	0.023*	-0.011*	0.004*	-0.003*	0.038*	0.000	-0.002*	-0.017*	-0.018*	0.105*		0.832*	0.409*	0.555*	0.427*	0.533*	0.173*	0.140*	-0.110*
DEATHS	0.035*	-0.027*	0.019*	-0.010*	0.005*	-0.001	0.031*	0.000	-0.002*	-0.013*	-0.018*	0.148*	0.779*		0.427*	0.435*	0.348*	0.506*	0.184*	0.137*	-0.123*
CONTAINMENT_ CLOSURE	0.122*	0.064*	0.020*	0.001*	-0.005*	0.002*	0.000	-0.001*	-0.003*	-0.012*	-0.005*	0.037*	0.426*	0.349*		0.380*	0.321*	0.888*	0.446*	0.431*	-0.122*
HEALTH_SYSTEM	0.064*	-0.032*	0.022*	-0.005*	-0.001*	-0.001	0.035*	0.001*	-0.004*	-0.018*	-0.010*	0.059*	0.562*	0.370*	0.568*		0.525*	0.679*	0.194*	0.157*	-0.104*
ECON_SUPPORT	0.057*	-0.029*	0.019*	-0.006*	0.005*	-0.003*	0.009*	-0.001*	-0.002*	-0.016*	-0.017*	0.037*	0.429*	0.308*	0.410*	0.602*		0.594*	0.224*	0.212*	-0.117*
GOV_RESPONSE	0.111*	0.023*	0.024*	-0.002*	-0.003*	0.001	0.014*	-0.001*	-0.004*	-0.017*	-0.010*	0.051*	0.552*	0.411*	0.911*	0.832*	0.667*		0.388*	0.354*	-0.157*
MEDIA_COVERAGE	0.104*	0.121*	0.014*	0.001*	0.000	0.003*	-0.017*	-0.004*	0.001	-0.007*	-0.009*	0.106*	0.192*	0.145*	0.518*	0.386*	0.297*	0.521*		0.885*	-0.206*
MEDIA_HYPE	0.101*	0.119*	0.009*	0.005*	-0.001*	0.000	-0.019*	-0.005*	-0.001*	-0.004*	-0.002*	-0.056*	0.148*	0.102*	0.493*	0.325*	0.255*	0.476*	0.902*		-0.174*
MEDIA_SENTIMENT	-0.021*	-0.058*	-0.008*	0.002*	-0.005*	-0.004*	0.009*	0.002*	-0.003*	0.003*	0.012*	-0.031*	-0.078*	-0.124*	-0.130*	-0.106*	-0.083*	-0.136*	-0.213*	-0.168*	

*Notes: This table presents Pearson-Spearman correlations. Measures above and below the diagonal represent Spearman and Pearson correlations, respectively. Values with *-indicator mark coefficients that are significant at $p < 0.05$. All variables are winsorized at the 1st and 99th percentiles.*

3.6.2 Government responses and stock returns

First, we examine whether the impact of COVID-19 on firms´ daily abnormal stock returns is moderated by the summarized government responses of countries that contribute to a firm´s revenue. Table 3 presents our main regression results for Equation 3.

Models I and II examine the raw impact of the growth rate of the announced number of confirmed COVID-19-positive cases [$CASES_{c,t}$] or deaths [$DEATHS_{c,t}$] per million associated with or caused by the disease on abnormal returns [$AR_{i,t+1}$]. As expected, results show that the stock market responds significantly negatively to both COVID-19 proxies. However, the daily growth in the number of country-specific deaths is of greater relevance to investors since the coefficient for $DEATHS_{c,t}$ (-0.063) is larger in magnitude than the coefficient for $CASES_{c,t}$ (-0.038). These findings are contrary to previous studies on the impact of COVID-19 cases and deaths on the stock market that expose cases to mainly drive the stock market (e.g., Alexakis et al. 2021; Ali et al. 2020; Erdem 2020; Zhang 2021). This contrast is most likely explained by the longer observation period that is considered in our study. Specially, when analyzing the consequences of diseases for the first time, a longer observation period allows for incorporating the different stages it passes. More specifically, in the initial period, the spread of the pandemic was mainly measured (and publicly discussed) by the increasing number of cases. In the course of the pandemic, this perspective changed due to worldwide high levels of cases, and deaths became a more important focus of interest for health organizations, governments, and news media. In addition, as is shown in Figure 3.1, the increase in the number of deaths was delayed compared to the increase in the number of cases. Hence, due to short observations covering the initial period of the pandemic, most preliminary studies lack enough data to reveal robust and interpretable results concerning deaths.

Our firm specific controls perform as expected and support the findings of the previous studies on stock market reaction we discussed. Turning to our media-related controls, we find MEDIA_COVERAGE and MEDIA_HYPE to show positive effects on stock returns. This is unsurprising since prior research on behavioral finance has well explored that the excessive presence of news, regardless of the expressed sentiment, leads to a higher attention of investors, and thus, gives positive momentum to the stock market development (e.g., Andrei and Halser 2015; Engelhardt et al. 2020). At the same time, MEDIA_SENTIMENT shows a significant and negative impact on stock returns. As this variable incorporates both positive and negative sentiment, and descriptive statistics reveal a mean of -5.930, and thus, predominantly negative sentiment throughout our observation period, this result follows prior research that finds negative news to negatively influence the stock markets (e.g., Cohen et al. 2018; Jung et al. 2018).

In Models III and IV, we add our summarized government response index [$GOV\_RESPONSE_{c,t}$] to analyze whether the entirety of a country´s responses to the pandemic moderates the association shown in the previous models. Across both models, we find positive and statistically significant coefficients on the moderation of cases and deaths by government responses. This indicates that the entirety of government policies positively influences investor sentiment, retriggers optimism, restores investor trust and eventually mitigates the decline of stock prices. In other words, market participants seem to appreciate governments´ efforts to contain the consequences of the pandemic. Our control variables follow similar patterns as in the previous models. Within each regression, F-tests indicate that the coefficients on the CASES/DEATHS and GOV_RESPONSE variables are significantly different from each other in all specifications, suggesting that both variables add explanatory value to our model.

Table 3.3: Government responses and stock returns

	(I)	(II)	(III)	(IV)
Dependent Variable		Abnormal Return [AR_{t+1}]		
CASES	-0.038***		-0.043***	
	(-125.203)		(-40.616)	
DEATHS		-0.063***		-0.184***
		(-81.551)		(-13.942)
GOV_RESPONSE			-0.000***	-0.025***
			(-2.912)	(-33.890)
CASES x GOV_RESPONSE			0.000***	
			(5.493)	
DEATHS x GOV_RESPONSE				0.031***
				(9.905)
VOLATILITY	0.017***	0.018***	0.017***	0.018***
	(5.910)	(6.088)	(5.919)	(6.033)
AR	0.037***	0.039***	0.037***	0.039***
	(72.478)	(77.118)	(72.460)	(76.430)
FOLLOWING	0.010***	0.010***	0.010***	0.010***
	(3.763)	(3.677)	(3.762)	(3.682)
INSTITUTIONAL	0.004	0.003	0.004	0.003
	(1.637)	(1.471)	(1.632)	(1.507)
SIZE	0.000	0.000	0.000	0.000
	(0.440)	(0.339)	(0.436)	(0.367)
PTB	-0.001***	-0.001***	-0.001***	-0.001***
	(-30.429)	(-34.522)	(-30.566)	(-33.306)
BOARD	0.058***	0.056***	0.058***	0.056***
	(4.825)	(4.674)	(4.819)	(4.712)
LEVERAGE	0.007***	0.006***	0.007***	0.007***
	(4.489)	(4.442)	(4.484)	(4.461)
ROA	-0.010	-0.008	-0.010	-0.009
	(-1.082)	(-0.851)	(-1.072)	(-0.919)
ESG	-0.006***	-0.006***	-0.006***	-0.006***
	(-5.258)	(-5.083)	(-5.251)	(-5.131)
REVENUE	-0.000	-0.000	-0.000	-0.000
	(-0.080)	(-0.033)	(-0.082)	(-0.031)
MEDIA_COVERAGE	0.003***	0.003***	0.003***	0.003***
	(38.495)	(33.332)	(35.795)	(40.035)

MEDIA_HYPE	0.001***	0.001***	0.001***	0.001***
	(14.073)	(12.261)	(14.047)	(12.826)
MEDIA_SENTIMENT	-0.003***	-0.003***	-0.003***	-0.003***
	(-54.836)	(-59.805)	(-55.117)	(-57.303)
Constant	-1.066***	-1.126***	-1.078***	-1.067***
	(-3.316)	(-3.500)	(-3.355)	(-3.316)
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,829,441	3,829,441	3,829,441	3,829,441
Adj. R2	0.0410	0.0388	0.0410	0.0391
F-test				
(CASES/DEATHS = GOV_RESPONSE)			<0.01	<0.01

*Notes: This table reports the regression results for the association between the daily growth in COVID-19 case [CASES] and death [DEATH] numbers and a firm´s abnormal returns [AR] both solely and depending on summarized government responses to the COVID-19 pandemic [GOV_RESPONSE]. See Appendix 3 for all variable definitions. Models I and II report the results for the impact of daily growth in cases and deaths, respectively. Models III and IV report the interaction with summarized government responses for the growth in the number of both cases and deaths. All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at firm level are presented in parentheses. *, **, *** indicate significance at 10, 5, and 1 percent based on two-tailed tests.*

3.6.3 Government responses split by scope and stock returns

Since we find summarized government responses to play an important role in stock market development during the COVID-19 pandemic, we are now interested in dividing our $GOV\_RESPONSE_{c,t}$ index into the different scopes of government responses, measured by our 16 country-specific indicators, to see whether different scopes of responses mitigate or reinforce the negative stock market impact of the pandemic. Table 2.4 presents the results of our regression models covering the moderating effects of government containment and closure policies [$CONTAINMENT\_CLOSURE_{c,t}$], the support of the country´s health system [$HEALTH\_SYSTEM_{c,t}$], and the support of the economy [$ECON\_SUPPORT_{c,t}$].

In Models I and II, we estimate the additional moderating effect of containment and closure policies in coherence with $CASES_{c,t}$ and $DEATHS_{c,t}$, respectively. Both interaction coefficients are positive and statistically significant. Hence, governments mitigate negative market impacts of the pandemic by taking actions to contain the spread of the disease, e.g., school closings, workplace closings, closings of public transport or issuing stay-at-home orders.

Government economic support [$ECON\_SUPPORT_{c,t}$] in Models V and VI has similar effects. Investors seem to appreciate the efforts of governments to mitigate the economic consequences of the pandemic by relieving debts and contracts or by supporting incomes. They most likely adjust their perceptions about market development and, in consequence, positively adjust their investment decisions.

Interestingly, government support of a country´s health system [$HEALTH\_SYSTEM_{c,t}$], shown in Models III and IV, causes further declines in abnormal stock returns as the interaction coefficients are negative and significant. For the interpretation of this counterintuitive effect, it is helpful to reinvestigate Figure 3.4. The pathway of the index for government efforts globally in supporting health systems [$HEALTH\_SYSTEM_{c,t}$] differs from the remaining two indices. From the date the WHO pronounced COVID-19 a pandemic on March 13, 2020 until the S&P 500 recovered to a preannouncement value on March 30, 2020, the growth of the health system index was significantly smaller, suggesting a smaller contribution to stock market declines. As the situation progressed, with recovering S&P 500 values, the health system index continued growing, while the other two indices showed persistent declines. Analyzing the index composition, one explanation may be the initial weakness and the delay of efforts in strengthening the health system. For example, widespread testing initiatives were implemented late due to the absence of reliable tests. This more obviously holds true for vaccination campaigns. Because health system policies are mainly implemented when the stock market was on a path of recovery and was gaining momentum, investors apparently feared restrictions or policies in the health sector that would interfere with the boom again. This uncertainty most likely provoked pessimism and, in consequence, negative stock market effects. Results from F-tests indicate a significant difference in the coefficients on CASES/DEATHS and the government response measures.

The coefficients of our sets of firm and country-specific control variables remain stable in significance, magnitude, and direction with indistinguishable differences from our previous regression covering summarizes government responses.

Table 3.4: Government responses by scope and stock returns

	(I)	(II)	(III)	(IV)	(V)	(VI)
Dependent Variable			Abnormal Return [AR_{t+1}]			
CASES	-0.073***		-0.077***		-0.033***	
	(-37.388)		(28.866)		(-42.144)	
DEATHS		-0.277***		-0.172***		-0.114***
		(-33.576)		(19.031)		(-45.422)
CONTAINMENT_CLOSURE	0.015*	-0.012***				
	(21.586)	(-18.660)				
HEALTH_SYSTEM			-0.008***	-0.035***		
			(-10.834)	(-49.668)		
ECON_SUPPORT					-0.026***	-0.039***
					(-50.218)	(-93.019)
CASES x CONTAINMENT_CLOSURE	0.007***					
	(15.514)					
DEATHS x CONTAINMENT_CLOSURE		0.053***				
		(26.712)				
CASES x HEALTH_SYSTEM			-0.034***			
			(-43.061)			
DEATHS x HEALTH_SYSTEM				-0.059***		
				(-24.756)		
CASES x ECON_SUPPORT					0.001***	
					(5.315)	
DEATHS x ECON_SUPPORT						0.019***
						(29.899)
VOLATILITY	0.017***	0.018***	0.017***	0.018***	0.017***	0.018***
	(5.866)	(6.026)	(5.933)	(6.027)	(5.915)	(6.005)
AR	0.037***	0.039***	0.036***	0.038***	0.036***	0.037***
	(72.001)	(76.540)	(71.132)	(75.180)	(70.534)	(72.156)
FOLLOWING	0.010***	0.010***	0.010***	0.010***	0.010***	0.009***
	(3.829)	(3.710)	(3.726)	(3.669)	(3.724)	(3.665)
INSTITUTIONAL	0.004*	0.003	0.003	0.003	0.004	0.003
	(1.693)	(1.524)	(1.609)	(1.511)	(1.615)	(1.520)
SIZE	0.000	0.000	0.000	0.000	0.000	0.000
	(0.468)	(0.374)	(0.333)	(0.311)	(0.409)	(0.357)
PTB	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-30.306)	(-33.608)	(-29.888)	(-32.371)	(-30.399)	(-32.756)
BOARD	0.058***	0.057***	0.057***	0.057***	0.057***	0.056***
	(4.883)	(4.733)	(4.816)	(4.731)	(4.779)	(4.676)
LEVERAGE	0.007***	0.007***	0.007***	0.007***	0.007***	0.006***
	(4.505)	(4.459)	(4.561)	(4.527)	(4.462)	(4.411)
ROA	-0.011	-0.009	-0.010	-0.009	-0.010	-0.009
	(-1.135)	(-0.929)	(-1.071)	(-0.940)	(-1.073)	(-0.947)

ESG	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(-5.307)	(-5.149)	(-5.254)	(-5.153)	(-5.242)	(-5.144)
REVENUE	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.074)	(-0.030)	(-0.066)	(-0.019)	(-0.102)	(-0.068)
MEDIA_COVERAGE	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(32.938)	(36.599)	(38.949)	(42.572)	(44.552)	(43.849)
MEDIA_HYPE	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(12.513)	(12.647)	(12.930)	(10.919)	(15.852)	(16.549)
MEDIA_SENTIMENT	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
	(-54.363)	(-56.592)	(-51.490)	(-55.408)	(-47.135)	(-45.855)
Constant	-1.086***	-1.105***	-1.049***	-1.037***	-1.044***	-1.067***
	(-3.381)	(-3.434)	(-3.265)	(-3.226)	(-3.249)	(-3.321)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,829,441	3,829,441	3,829,441	3,829,441	3,829,441	3,829,441
Adj. R2	0.0412	0.0390	0.0415	0.0396	0.0418	0.0409
F-test						
CASES/DEATHS= CONTAINMENT_CLOSURE	<0.01	<0.01				
HEALTH_SYSTEM			<0.01	<0.01		
ECON_SUPPORT					<0.01	<0.01

*Notes: This table reports the regression results for the association between the daily growth in COVID-19 case [CASES] and death [DEATH] numbers and a firm´s abnormal returns [AR] and the dependence of split government responses to the COVID-19 pandemic in the fields of containment and closure [CONTAINMENT_CLOSURE], health system policies [HEALTH_SYSTEM], and economic support [ECON_SUPPORT]. See Appendix 3 for all variable definitions. Models I and II report the results for the interaction of the daily growth in cases and deaths with containment and closure policies. Models III and IV report the interaction of the daily growth in cases and deaths with health system policies, and Models V and VI report the interaction of the daily growth in cases and deaths with government economic support. All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at firm level are presented in parentheses. *, **, *** indicate significance at 10, 5, and 1 percent based on two-tailed tests.*

3.6.4 Government responses and firm-specific COVID-19 revenue exposure

In contrast to most studies on the economic consequences of the COVID-19 pandemic we discussed, we investigate COVID-19 related impacts on firm-level rather than aggregating an entire economy. This approach allows a detailed investigation of the linkage between the COVID-19 pandemic, worldwide government regulations, and multinational firms´ characteristics.

One major field of interest for both research and practice is whether some firms are more severely affected by the COVID-19 pandemic and by government responses than others. Recent studies show various firm-specific characteristics to moderate the extent of the declines in stock returns associated with the pandemic. For example, Ding et al. (2020) find that firms with high exposure to supply chain disruptions show greater stock price declines.

We aim to analyze whether country-specific sales revenues at the firm level influence the effect of governmental responses to COVID-19-associated stock market effects. Specifically, we are interested in whether investors react differently to a growth in the number of COVID-19 cases and deaths and related government responses when a firm is more severely affected by this growth on the sales side.

We employ the comprehensive *FactSet Geographic Revenue Exposure (GeoRev)* Database that meters a firm´s annual sales revenue for each of the world's countries it operates in. The data is derived from a broad set of sources, e.g., summarized annual reports. In addition, 'an estimation algorithm based on GDP weighting and accounting logic is then applied to solve for any non-explicit disclosures.' (FactSet 2022) The result is a detailed breakdown of a company´s revenues into any geographic country. The database also provides a certainty score that is based on source metadata and ranges from 1 (low certainty) to 80 (declared value). We only include values with a certainty score of 70 or above.

We assume, that for each firm, country-specific revenues reflect the importance of a country to the firm´s economy. The risk of losing revenue in a country may increase when the COVID-19 pandemic´s intensity is high. To combine both the importance of a country for a firm´s revenues and the risk of losses in a country, we calculate an indicator for firm-country-level sales revenue exposure to the pandemic. Thus, $EXPOSURE_{i,t}$ is the country-specific sales revenues of our sample firms [$REVENUE_{i,c,t}$], weighted by country´s daily growth rates of COVID-19 cases [$CASES_{c,t}$] and deaths [$DEATHS_{c,t}$] per million. For instance, a high infection or death rate in a country that does not significantly contribute to a firm´s sales revenues may not be considered as a threat to that firm. The same may holds true for a country that highly contributes to the firm´s sales revenue but shows low infection rates.

The variable is then standardized using z-scores and normalized to a scale from 0 to 100, where higher values indicate a larger firm-specific revenue exposure to COVID-19. For example, a value of 100 would be related to a firm-day observation if the growth in COVID-19 cases or deaths among all firm-relevant countries is the highest in the countries that contribute most to the firm´s revenues. In the same way, a value of 0 would be related to a firm-day observation if there is no growth in COVID-19 cases or deaths among all countries that contribute to a firm´s revenues. We make the following adjustments to our regression model in Equation (4):

$$\mathbf{AR_{i,t+1} = \beta_0 + \beta_1 * COVID\text{-}19_{c,t} + \beta_2 * RESPONSE_{c,t} + \beta_3 * EXPOSURE_{i,t} + \beta_4 * COVID\text{-}19_{c,t} \times RESPONSE_{c,t} \times EXPOSURE_{i,t} + \Sigma\ Controls_{i,c,t} + Firm\ FE_i + Day\ FE_t + \varepsilon_{i;t}} \tag{4}$$

where i, c, and t index firm, country, and day, respectively.

Results are presented in Table 2.5, where Panels A and B observe $CASES_{c,t}$ and $DEATHS_{c,t,}$ respectively, as proxies for COVID-$19_{c,t}$.

In Panel A Model I, the three-way interaction reveals that the mitigating effect of summarized government responses [$GOV\_RESPONSE_{c,t}$], as shown previously, is even stronger for firms that are highly exposed to COVID-19 on the sales side. The coefficient is positive and significant but shows a low magnitude.

The same holds true for governmental efforts in economic support [$ECON\_SUPPORT_{c,t}$], presented in Model IV. In contrast, containment and closure policies [$CONTAINMENT\_CLOSURE_{c,t}$] (Model II) seem to be rated differently by investors in the case that a firm´s revenue is highly exposed to COVID-19. While in our main regression model with split government responses by scope, containment and closure policies mitigate stock price declines due to growing COVID-19 case numbers, they seem not strong enough to do so if a firm achieves high sales revenues in countries that are highly affected by the pandemic.

Turning to health system policies [HEALTH_SYSTEMc,t] (Model III), government support seems to be rated more positively when investors are more severely affected by the pandemic. Moreover, the additional positive effect of government health system policies for firms that are highly exposed to the pandemic (coefficient 0.033) even reverses the initial negative effect (coefficient -0.015), where the moderation of $EXPOSURE_{c,t}$ was unconsidered. Thus, investors of firms with high COVID-19 revenue exposure aim for a fast recovery and positively assess health system policies, regardless of consequential restrictions. In Panel B, $COVID\text{-}19_{c,t}$ is represented by $DEATHS_{c,t.}$ For all models, the results are similarly directed. As a sole exception, we fail to find a significant three-way interaction for the economic support index.

Table 3.5 Panel A: Government responses and firm-specific COVID-19 revenue exposure [CASES]

	(I)	(II)	(III)	(IV)
Dependent Variable		Abnormal Return [AR_{t+1}]		
CASES	-0.041***	-0.058***	-0.041***	-0.031***
	(-28.423)	(-22.357)	(9.393)	(-34.138)
EXPOSURE	0.041***	-0.034***	0.808***	0.047***
	(7.636)	(-3.403)	(45.111)	(13.170)
CASES x EXPOSURE	-0.004***	0.011***	-0.138***	-0.010***
	(-3.469)	(5.667)	(-38.297)	(-12.538)
GOV_RESPONSE	-0.001***			
	(-16.633)			
CONTAINMENT_CLOSURE		0.001*		
		(1.670)		
HEALTH_SYSTEM			-0.013***	
			(-17.015)	
ECON_SUPPORT				-0.026***
				(-52.973)
CASES x GOV_RESPONSE	0.000***			
	(14.821)			
CASES X CONTAINMENT_CLOSURE		0.009***		
		(13.367)		
CASES x HEALTH_SYSTEM			-0.015***	
			(-14.150)	
CASES x ECON_SUPPORT				0.005***
				(19.937)
GOV_RESPONSE x EXPOSURE	-0.001***			
	(-9.987)			
CONTAINMENT_CLOSURE x EXPOSURE		0.005*		
		(1.875)		
HEALTH_SYSTEM x EXPOSURE			-0.196***	
			(-46.008)	
ECON_SUPPORT x EXPOSURE				-0.012***
				(-13.689)
CASES x GOV_RESPONSE x EXPOSURE	0.000***			
	(4.515)			
CASES x CONTAINMENT_CLOSURE x EXPOSURE		-0.002***		
		(-4.912)		
CASES x HEALTH_SYSTEM x EXPOSURE			0.033***	
			(39.226)	
CASES x ECON_SUPPORT x EXPOSURE				0.002***
				(10.871)
CONTROLS	Yes	Yes	Yes	Yes
Constant	-0.247***	-0.257***	-0.230***	-0.238***
	(-33.948)	(-35.102)	(-30.807)	(-32.872)
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,829,441	3,829,441	3,829,441	3,829,441
Adj. R2	0.0256	0.0255	0.0266	0.0264
F-test				
CASES=EXPOSURE	<0.05	<0.01	<0.01	<0.05
CASES=GOV_RESPONSE/CONTAINMENT_CLOSURE/ HEALTH_SYSTEM/ECON_SUPPORT	<0.01	<0.01	<0.01	<0.01
EXPOSURE= GOV_RESPONSE/CONTAINMENT_CLOSURE/ HEALTH_SYSTEM/ECON_SUPPORT	<0.01	<0.05	<0.01	<0.01

Table 3.5 Panel B: Government responses and firm-specific COVID-19 revenue exposure [DEATHS]

	(I)	(II)	(III)	(IV)
Dependent Variable		Abnormal Return [AR_{t+1}]		
DEATHS	-0.132***	-0.233***	-0.013***	-0.108***
	(-22.084)	(-17.480)	(-0.790)	(-30.839)
EXPOSURE	-0.024***	-0.060***	0.310***	0.001
	(-8.861)	(-11.902)	(33.241)	(0.588)
DEATHS x EXPOSURE	0.028***	0.052***	-0.063***	0.002
	(12.764)	(9.832)	(-8.934)	(1.269)
GOV_RESPONSE	-0.001***			
	(-32.539)			
CONTAINMENT_CLOSURE		-0.008***		
		(-12.873)		
HEALTH_SYSTEM			-0.025***	
			(-34.979)	
ECON_SUPPORT				-0.027***
				(-66.425)
DEATHS x GOV_RESPONSE	0.001***			
	(17.291)			
DEATHS X CONTAINMENT_CLOSURE		0.047***		
		(14.631)		
DEATHS x HEALTH_SYSTEM			-0.006	
			(-1.496)	
DEATHS x ECON_SUPPORT				0.023***
				(25.318)
GOV_RESPONSE x EXPOSURE	-0.000			
	(-0.262)			
CONTAINMENT_CLOSURE x EXPOSURE		0.008***		
		(6.173)		
HEALTH_SYSTEM x EXPOSURE			-0.079***	
			(-36.098)	
ECON_SUPPORT x EXPOSURE				-0.005***
				(-8.881)
DEATHS x GOV_RESPONSE x EXPOSURE	0.000***			
	(-9.930)			
DEATHS x CONTAINMENT_CLOSURE x EXPOSURE		-0.011***		
		(-8.380)		
DEATHS x HEALTH_SYSTEM x EXPOSURE			0.017***	
			(10.324)	
DEATHS x ECON_SUPPORT x EXPOSURE				0.000
				(0.439)
CONTROLS	Yes	Yes	Yes	Yes
Constant	-0.252***	-0.259***	-0.213***	-0.247***
	(-34.690)	(-35.463)	(-28.628)	(-34.084)
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,829,441	3,829,441	3,829,441	3,829,441
Adj. R2	0.0251	0.0249	0.0258	0.0262
F-test				
DEATHS=EXPOSURE	<0.05	<0.05	<0.01	<0.01
DEATHS=GOV_RESPONSE/CONTAINMENT_CLOSURE/	<0.01	<0.01	<0.01	<0.01
EXPOSURE= GOV_RESPONSE/CONTAINMENT_CLOSURE/	<0.01	<0.01	<0.01	<0.01

*Notes: This table reports the regression results for the association between the daily growth in the number of COVID-19 cases [CASES] and deaths [DEATH] and a firm´s abnormal returns [AR] depending on (1) summarized government responses [GOV_RESPONSES] and split government responses to the COVID-19 pandemic in the fields of containment and closure [CONTAINMENT_CLOSURE], health system policies [HEALTH_SYSTEM], and economic support [ECON_SUPPORT] and (2) a firm´s specific daily revenue exposure to COVID-19 [EXPOSURE]. See Appendix 3 for all variable definitions. In Panel A, Model I presents the results for the interaction of the daily growth in COVID-19 case numbers with summarized government responses to the COVID-19 pandemic. Models II to IV report the interaction of the daily growth in COVID-19 case numbers with containment and closure policies (Model II), health system policies (Model III), and government economic support (Model IV). In Panel B, Model I presents the results for the interaction of the daily growth in COVID-19 death numbers with summarized government responses to the COVID-19 pandemic. Models II to IV report the interaction of the daily growth in COVID-19 death numbers with containment and closure policies (Model II), health system policies (Model III), and government economic support (Model IV). All continuous variables are winsorized to the 1st and 99th percentiles of their distributions. The t-statistics from robust standard errors clustered at the firm level are presented in parentheses. *, **, *** indicate significance at 10, 5, and 1 percent based on two-tailed tests.*

3.6.5 Estimation of COVID-19 growth rates with an epidemiological standard model

In our main regression models, we employ the percentage growth rates for both COVID-19 cases and deaths to proxy for the spread of the COVID-19 pandemic. Specifically, for the increase in COVID-19 cases and deaths, we consider the growth rate of the announced cumulative number of confirmed COVID-19-positive cases per million and country and the growth rate of the announced deaths associated or caused by COVID-19 per million and country, respectively. However, this perspective assumes a linear progression of the pandemic.

In fact, as graphically visible in Figure 3.1, the spread of COVID-19 can be separated into two phases: exponential growth of cases and deaths corresponding to initial global outbreaks, followed by logistic progression due to mitigated infection rates as global government responses unfold (De Silva et al. 2012). Epidemiological standard models can be used to address this nonlinearity. Comparing the performance of standard models for fast epidemics, Ma (2020) shows that the *susceptible-infectious-recovered model (SIR)*, first published by Hethcote (1989), provides a robust estimate for the spread of a disease exhibiting a pattern similar to COVID-19. SIR assumes the immunity of recovered individuals and incorporates the number of susceptible individuals. We calculate the SIR growth rate following Ma (2020) and Furtado (2021) as

$$\begin{aligned} \frac{\mathbf{dS(t)}}{\mathbf{dt}} &= -\frac{\text{ß}}{\mathbf{N}}\mathbf{I(t)S(t)} \\ \frac{\mathbf{dI(t)}}{\mathbf{dt}} &= \frac{\text{ß}}{\mathbf{N}}\mathbf{I(t)S(t)} - \mathbf{yI(t)} \\ \frac{\mathbf{dR(t)}}{\mathbf{dt}} &= \mathbf{yI(t)} \end{aligned} \tag{5}$$

where *S* is the share of susceptible individuals, *I* is the share of infectious individuals, and *R* is the share of recovered individuals. *ß* is the transmission rate per infectious individual, and *y* is the recovery rate. With the total number of individuals kept constant as the sum of *S*, *I*, and *R*, the expected growth rate is calculated as $\lambda = ß - y$. Descriptive statistics provide a mean of 4.531%. We recalculate our regression models, substituting our measures for the spread of the disease, i.e., $CASES_{c,t,}$ by the SIR growth rate. Untabulated results remain congruent within all our regression models, indicating no distortion due to an imprecise, exponential fit of our COVID-19 proxies.

3.7 Robustness Tests

Alternative Benchmarks for the Measurement of Abnormal Returns

Clearly, our study covers a worldwide economic crises that, without precedent, can be expected to systematically affect almost all sectors and firms worldwide. Thus, it is particularly important to find a benchmark for a firm´s returns that does not ignore the overarching effects of the crisis and is free of systematic influences. Thus, we employ three alternative approaches for the calculation of abnormal stock returns.

First, we recalculate our models using the daily average market return of the entire US market instead of focusing on the S&P 500. Therefore, we obtain the daily index prices of the Dow Jones U.S. Total Stock Market Index for our observation period. The index measures all U.S. equity issues with available prices and covers 4,224 firms and ten sectors. Similar to our main regression, we define the market adjustment of raw returns as $\boldsymbol{AR_t^i} = \boldsymbol{R_t^i} - \boldsymbol{E}\left(\boldsymbol{R_t^i}\right)$, where $\boldsymbol{R_t^i}$ represents the daily return for firm *i* on day *t*. We estimate the firm´s expected return as $\boldsymbol{E(R_t^i)} = \boldsymbol{\alpha_i} + \boldsymbol{b_i} * \boldsymbol{E(R_t^{market})}$, with $\boldsymbol{R_t^{market}} = (\boldsymbol{P_t^{market}} - \boldsymbol{P_{t-1}^{market}})/\boldsymbol{P_{t-1}^{market}}$, where $\boldsymbol{P_t^{market}}$ now represents the Dow Jones U.S. Total Stock Market

Index closing price on day *t*. As all estimates are statistically indistinguishable from one another, evidence is provided for our main model´s results.

Second, we apply a portfolio-based approach to incorporate firm-specific risk instead of simply observing the daily market average. Specifically, following Fama and French (1995) and Kothari and Warner (2004), we compute a firm’s abnormal returns by adjusting the total returns for factors that have been found to explain cross-sectional differences in stock returns, i.e., a firm’s market capitalization and its price-to-book ratio. Similar to Brav *et al.* (2000), we form a set of floating portfolios of firms, with each portfolio expressing a distinct range of firm-size, i.e., a firm´s capitalization. Within each portfolio, we rank the firms by their price-to-book ratio. Based on our ranking values, we define a weighting factor $\boldsymbol{w_j}$ for each ranking position. Total returns $\boldsymbol{R_t^i}$ are then adjusted by the weighted total returns with varying values for each observation day: $\boldsymbol{AR_t^i = R_t^i - R_t^{i,port}}$. Following Sul *et al.*, (2014), we calculate $\boldsymbol{R_t^i}$ as the natural logarithm of total returns plus one: $\boldsymbol{R_t^i = ln\left(R_t^i + 1\right)}$. $\boldsymbol{R_t^{i,port}}$ therefore, can be defined as $\boldsymbol{\frac{1}{n} \sum_{j=1}^{n} w_j \left(R_t^i\right)}$, where the sum of weights in each portfolio equals 1 ($\boldsymbol{\sum_{j=1}^{n} w_j = 1}$). All results remain unchanged in direction and show insignificant divergences in magnitude.

Aggregation of Country-Specific Data on Firm Level

Our research design employs daily firm-country specific data. This approach carries important benefits that help to get deeper insights into the role of country-specific government responses when analyzing the pandemic´s impact on firms. Specifically, for each firm, we consider all countries worldwide that contribute to the firm´s revenues within our observation period. As a result, we split each firm into a set of pseudo-subsidiaries, with each subsidiary to solely reflect the effects of government responses of a single, distinct country on the firm´s stock prices over time.

In addition, the approach includes several country-specific control variables, e.g., media-sentiment variables, that continuously measure the spread and tone of pandemic-related news in a country. Following prior research that we discussed beforehand, they may be considered important drivers of investor sentiment.

However, a straightforward way of analyzing our dataset is to aggregate all data at the firm level. Specifically, on firm level, we weight a country´s daily COVID-19 related case and death numbers with its intensity of government responses. The result is a global variable for the overall strength of COVID-19 government policies for each firm. In this approach, again, all countries that contribute to the firm's sales revenues, are included. This calculation is blurred since it averages the country-specific government responses and the COVID-19 measures worldwide. However, it may still reinforce the robustness of our research design. We recalculate our regression models, using the aggregated data on firm level. Results remain unaffected and show similar magnitudes and directions.

Further Robustness Tests

We perform further robustness tests to validate the results of our regression models. First, we include country-fixed effects to control for country-level heterogeneity. Again, results remain unchanged in direction and magnitude. Second, to control for cross-effects indicating that abnormal stock returns influence government responses, we repeat all regressions using $RESPONSE_{c,t}$ as the dependent variable. We do not find significant results, supporting our main findings. Third, we conduct an in-time placebo test using placebo time windows to ensure that our regression results are not driven by our research design (e.g., Conley and Taber 2011; Hahn and Shi 2017). We run our main regression model shifting all independent variables back and forth 10, 15 and 30 trading days, respectively, holding our dependent variable, abnormal returns, constant. We fail to find any significant results, suggesting that, assuming no treatment effects, there is no evidence of random or systematic errors due to a weak model design. Forth, the reported results remain stable when conducting random effect regressions. Fifth, we use altering data frequencies to assure that our results are not sensitive to to the daily-data approach. We aggregate all variables both weekly and monthly and rerun our main regressions. Results do not reveal divergences. Sixth, we recalculate our analysis substituting our dependent variable, abnormal returns, with raw returns. Results follow similar patterns throughout all models.

3.8 Conclusion

In this paper, we analyze the role of worldwide government efforts to contain the spread and the economic consequences of the COVID-19 pandemic in shaping investor sentiment and stock market reactions. We explore the impact of government responses in the three fields of containment and closure, health system policies, and economic support of 180 countries on the relationship between growth rates of COVID-19 cases and deaths and firm-specific S&P 500 abnormal stock returns in a period from 1st January 2020 to 15th March 2021. We further investigate weather investor´s behavior is sensitive to a firm´s revenue exposure to

COVID-19. We employ both an exponential growth model and an epidemiological standard model to account for the different stages of the pandemic and to address the nonlinear spread of the disease.

In contrast to previous studies, we find that deaths mainly drive stock returns during the COVID-19 pandemic. Undifferentiated, the entirety of government responses mitigates the decline of stock prices as market participants appreciate governments´ efforts to contain the consequences of the pandemic. Split by the different scopes of government responses, governments may mitigate negative market impacts caused by the pandemic by taking actions in the field of containment and closure, e.g., by school closings, workplace closings, closings of public transport or issuing stay-at-home orders. Similar effects stem from government´s economic support. Government support of a country´s health system provokes further declines in abnormal stock returns.

Analyzing the moderation of a firm´s revenue exposure to COVID-19, the mitigating effect of the entirety of government responses is even stronger for firms that are highly exposed to COVID-19 on the sales side. Differentiated by scope, this holds true for the field of government economic support. Containment and closure policies do not seem strong enough for investors to adjust their pessimistic views on market development. Hence, we find no mitigation of stock price declines due to growing COVID-19 case numbers. Contrary to our initial findings, government support of health systems is rated more positively by investors when a firm is more severely affected by the pandemic on the sales side. The additional positive stock market effect for firms that are highly exposed to the pandemic even reverses the initial negative impact. These results remain unchanged when the spread of COVID-19 is estimated using an epidemiological standard model, i.e., the SIR, to account for the pandemic´s nonlinear course.

Our findings contribute to both practice and research. First, firms that become aware of both the pandemic´s impact on investor sentiment and the moderating role of government responses may be able to anticipate and strategically manage investor relations. Regarding investors´ reactions to a firm’s country-specific revenue exposure to COVID-19, firms should aim to redirect and adjust the content and scope of their communications with investors. They may also aim for a dialog with governments to encourage aid in firm-relevant fields. Second, our results are relevant for government regulators debating the economic costs and benefits of government responses to pandemics, since no case of such extent is yet known, and reliable data concerning the consequences of government interventions for medical crises are rare. Third, our study expands the knowledge about investor sentiment as a driver of stock prices during external shocks followed by crisis situations.

As with all studies, our study is limited in several ways and, as such, paves the way for future research. As we derive investor sentiment indirectly by measuring abnormal stock market reactions, qualitative studies will be necessary to more deeply investigate investors’ behavior during the COVID-19 pandemic. Although investor reactions are clearly visible, the psychological motives as well as the strength, composition, and persistence of investor reactions remain unclear and require further investigation. We analyze whether investor´s perceptions of government responses to the COVID-19 pandemic are affected by the share of sales revenues that is threatened by the pandemic in each country. However, this approach compromises several weaknesses since the linkage between the case and death development and sales revenue may not be linear. We encourage further research to build on this bias and seek for more accurate approaches to reflect the risk of losing sales revenues during pandemics. Moreover, we do not analyze whether firm characteristics other than country-specific sales revenues may mitigate or reinforce stock market reactions. For example, the exposure of worldwide supply chains may cause different effects on the stock market and, thus, should be a matter of further research. As our dataset provides firm-country-specific data, further studies may cluster countries and reveal the role of policies and measures among geographic regions or political and economical unions.

Appendix 3.1

Country-specific S&P 500 firm allocation (1-100)

No.	Country	Number of Firms	Share of S&P 500	No.	Country	Number of Firms	Share of S&P 500
1	Afghanistan	154	30.14	51	El Salvador	195	38.16
2	Albania	190	37.18	52	Eritrea	44	8.61
3	Algeria	251	49.12	53	Estonia	249	48.73
4	Andorra	9	1.76	54	Ethiopia	234	45.79
5	Angola	237	46.38	55	Faroe Islands	9	1.76
6	Argentina	289	56.56	56	Fiji	17	3.33
7	Aruba	21	4.11	57	Finland	308	60.27
8	Australia	312	61.06	58	France	331	64.77
9	Austria	316	61.84	59	Gabon	136	26.61
10	Azerbaijan	223	43.64	60	Gambia	2	0.39
11	Bahamas	103	20.16	61	Georgia	198	38.75
12	Bahrain	220	43.05	62	Germany	334	65.36
13	Bangladesh	283	55.38	63	Ghana	226	44.23
14	Barbados	40	7.83	64	Greece	303	59.30
15	Belarus	278	54.4	65	Guam	20	3.91
16	Belgium	320	62.62	66	Guatemala	249	48.73
17	Belize	12	2.35	67	Guinea	114	22.31
18	Benin	123	24.07	68	Guyana	45	8.81
19	Bermuda	47	9.2	69	Haiti	64	12.52
20	Bhutan	13	2.54	70	Honduras	184	36.01
21	Bolivia	232	45.4	71	Hungary	310	60.67
22	Bosn. & Herzeg.	206	40.31	72	Iceland	226	44.23
23	Botswana	149	29.16	73	India	310	60.67
24	Brazil	305	59.69	74	Indonesia	279	54.60
25	Brunei Darussalam	102	19.96	75	Iran	269	52.64
26	Bulgaria	284	55.58	76	Iraq	264	51.66
27	Burkina Faso	135	26.42	77	Ireland	322	63.01
28	Burundi	12	2.35	78	Israel	275	53.82
29	Cabo Verde	2	0.39	79	Italy	325	63.60
30	Cambodia	194	37.96	80	Jamaica	131	25.64
31	Cameroon	207	40.51	81	Japan	315	61.64
32	Canada	350	68.49	82	Jordan	222	43.44
33	Cent. Afr. Rep.	2	0.39	83	Kazakhstan	262	51.27

34	Chad	98	19.18	84	Kenya	237	46.38
35	Chile	287	56.16	85	Kiribati	1	0.20
36	Colombia	288	56.36	86	Kuwait	258	50.49
37	Congo	92	18	87	Kyrgyzstan	73	14.29
38	Costa Rica	244	47.75	88	Laos	168	32.88
39	Cote d'Ivoire	222	43.44	89	Latvia	260	50.88
40	Croatia	283	55.38	90	Lebanon	232	45.40
41	Cuba	246	48.14	91	Lesotho	5	0.98
42	Cyprus	229	44.81	92	Liberia	7	1.37
43	Czech Republic	315	61.64	93	Libya	218	42.66
44	Denmark	312	61.06	94	Liechtenstein	93	18.20
45	Djibouti	10	1.96	95	Lithuania	280	54.79
46	Dominica	4	0.78	96	Luxembourg	293	57.34
47	Dom. Republic	245	47.95	97	Madagascar	122	23.87
48	DR of the Congo	216	42.27	98	Mainland China	324	63.41
49	Ecuador	262	51.27	99	Malawi	55	10.76
50	Egypt	272	53.23	100	Malaysia	281	54.99

Country-specific S&P 500 firm allocation (101-180)

No.	Country	Number of Firms	Share of S&P500	No.	Country	Number of Firms	Share of S&P500
101	Mali	141	27.59	151	Sudan	187	36.59
102	Malta	193	37.77	152	Suriname	27	5.28
103	Mauritania	49	9.59	153	Swaziland	24	4.70
104	Mauritius	124	24.27	154	Sweden	315	61.64
105	Mexico	317	62.04	155	Switzerland	317	62.04
106	Moldova	166	32.49	156	Syria	232	45.40
107	Monaco	101	19.77	157	Tajikistan	69	13.50
108	Mongolia	115	22.50	158	Tanzania	225	44.03
109	Morocco	247	48.34	159	Thailand	298	58.32
110	Mozambique	135	26.42	160	Timor-Leste	10	1.96
111	Myanmar	254	49.71	161	Togo	37	7.24
112	Namibia	120	23.48	162	Tonga	2	0.39
113	Nepal	209	40.90	163	Trinidad and Tobago	171	33.46
114	Netherlands	326	63.80	164	Tunisia	201	39.33
115	New Zealand	274	53.62	165	Turkey	277	54.21
116	Nicaragua	104	20.35	166	Turkmenistan	226	44.23
117	Niger	110	21.53	167	Uganda	200	39.14

118	Nigeria	263	51.47
119	Norway	309	60.47
120	Oman	240	46.97
121	Pakistan	266	52.05
122	Palestine	126	24.66
123	Panama	242	47.36
124	Papua New Guinea	167	32.68
125	Paraguay	233	45.60
126	Peru	281	54.99
127	Philippines	273	53.42
128	Poland	322	63.01
129	Portugal	310	60.67
130	Puerto Rico	254	49.71
131	Qatar	262	51.27
132	South Korea	308	60.27
133	Romania	310	60.67
134	Russian Federation	318	62.23
135	Rwanda	88	17.22
136	San Marino	3	0.59
137	Saudi Arabia	274	53.62
138	Senegal	168	32.88
139	Serbia	269	52.64
140	Seychelles	1	0.20
141	Sierra Leone	16	3.13
142	Singapore	304	59.49
143	Slovakia	298	58.32
144	Slovenia	279	54.60
145	Solomon Islands	7	1.37
146	Somalia	48	9.39
147	South Africa	268	52.45
148	South Sudan	7	1.37
149	Spain	327	63.99
150	Sri Lanka	256	50.10
168	Ukraine	299	58.51
169	United Arab Emirates	276	54.01
170	United Kingdom	355	69.47
171	United States	501	98.04
172	Uruguay	248	48.53
173	US Virgin Islands	31	6.07
174	Uzbekistan	233	45.60
175	Vanuatu	2	0.39
176	Venezuela	254	49.71
177	Vietnam	284	55.58
178	Yemen	187	36.59
179	Zambia	166	32.49
180	Zimbabwe	155	30.33

Notes: This table provides the distribution of included firms by country. A firm is assigned to a country if the country contributes to the firm´s sales revenues. The share of S&P 500 firms that exhibit revenue in the specific country is displayed in the right column. We use country-specific sales revenue data for the compounding S&P 500 firms for 2019 from the FactSet Geographic Revenue (GeoRev) Database. We only include values with a certainty score of 70 or above, as provided by GeoRev. The certainty score is based on source metadata and ranges from 1 (low certainty) to 80 (declared value).

Appendix 3.2

List of indicator descriptions and scale codings

Name	Description	Coding
Containment and closure policies		
School closing	Record closings of schools and universities	0 - no measures 1 - recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 - require closing (only some levels or categories, e.g., just high school or just public schools) 3 - require closing all levels Blank - no data
Workplace closing	Record closings of workplaces	0 - no measures 1 - recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation 2 - require closing (or work from home) for some sectors or categories of workers 3 - require closing (or work from home) for all-but-essential workplaces (e.g., grocery stores, doctors) Blank - no data
Cancel public events	Record canceling public events	0 - no measures 1 - recommend canceling 2 - require canceling Blank - no data
Restrictions on gatherings	Record limits on gatherings	0 - no restrictions 1 - restrictions on very large gatherings (above 1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings of 10 people or less Blank - no data
Close public transport	Record closing of public transport	0 - no measures 1 - recommend closing (or significantly reducing volume/route/means of transport available) 2 - require closing (or prohibit most citizens from using it) Blank - no data
Stay at home requirements	Record orders to "shelter-in-place" and otherwise confine to the home	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips 3 - require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc.) Blank - no data

Restrictions on internal movement	Record restrictions on internal movement between cities/regions	0 - no measures 1 - recommend no travel between regions/cities 2 - internal movement restrictions in place Blank - no data
International travel controls	Record restrictions on international travel Note: this records policy for foreign travelers, not citizens	0 - no restrictions 1 - screening arrivals 2 - quarantine arrivals from some or all regions 3 - ban arrivals from some regions 4 - ban on all regions or total border closure Blank - no data
Health system policies		
Public information campaigns	Record presence of public info campaigns	0 - no Covid-19 public information campaign 1 - public officials urging caution about Covid-19 2- coordinated public information campaign (e.g., across traditional and social media) Blank - no data
Testing policy	Record government policy on who has access to testing Note: this records policies about testing for current infection (PCR tests) not testing for immunity (antibody test)	0 - no testing policy 1 - only those who both (a) have symptoms AND (b) meet specific criteria (e.g., key workers, admitted to hospital, came into contact with a known case, returned from overseas) 2 - testing of anyone showing Covid-19 symptoms 3 - open public testing (e.g., "drive through" testing available to asymptomatic people) Blank - no data
Contact tracing	Record government policy on contact tracing after a positive diagnosis Note: policies that would identify all people potentially exposed to Covid-19; voluntary bluetooth apps are unlikely to achieve this	0 - no contact tracing 1 - limited contact tracing; not done for all cases 2 - comprehensive contact tracing; done for all identified cases
Facial coverings	Record policies on the use of facial coverings outside the home	0 - No policy 1 - Recommended 2 - Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible 3 - Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible 4 - Required outside the home at all times regardless of location or presence of other people
Vaccination policy	Record policies for vaccine delivery for different groups	0 - No availability 1 - Availability for ONE of following: key workers/clinically vulnerable groups (non-elderly)/elderly groups 2 - Availability for TWO of following: key workers/clinically vulnerable groups (non-elderly)/elderly groups 3 - Availability for ALL of following: key workers/clinically vulnerable groups (non-elderly)/elderly groups

		4 - Availability for all three plus partial additional availability (select broad groups/ages) 5 - Universal availability
Protection of elderly people	Record policies for protecting elderly people (as defined locally) in long term care facilities (LTCF) and/or community and home settings	0 - no measures 1 - Recommended isolation, hygiene, and visitor restriction measures in LTCFs and/or elderly people to stay at home 2 - Narrow restrictions for isolation, hygiene in LTCFs, some limitations on external visitors and/or restrictions protecting elderly people at home 3 - Extensive restrictions for isolation and hygiene in LTCFs, all nonessential external visitors prohibited, and/or all elderly people required to stay at home and not leave the home with minimal exceptions, and receive no external visitors Blank - no data
Economic support		
Income support (for households)	Record if the government is providing direct cash payments to people who lose their jobs or cannot work. Note: only includes payments to firms if explicitly linked to payroll/salaries	0 - no income support 1 - government is replacing less than 50% of lost salary (or if a flat sum, it is less than 50% of median salary) 2 - government is replacing 50% or more of lost salary (or if a flat sum, it is greater than 50% of median salary) Blank - no data
Debt/contract relief (for households)	Record if the government is freezing financial obligations for households (e.g., stopping loan repayments, preventing services like water from being stopped, or banning evictions)	0 - no debt/contract relief 1 - narrow relief, specific to one kind of contract 2 - broad debt/contract relief

Notes: This table provides the descriptions and scale codings of all indicators composing the indices for our three policy fields, i.e., containment and closure index, health system index, and economic support index. To create the indices, subindices are calculated for all indicators to normalize each indicator to an equally spaced scale between 0 and 100. The three indices are then calculated as simple averages of the normalized individual subindices. This table is provided by Oxford University´s Government Response Tracker (OxCGRT).

Appendix 3.3

Variable definitions

Variables	Definition	Level	Frequency	Data Source
Dependent Variable				
AR	Adjusted abnormal logarithmic returns based on a single-index market model. Expected returns are estimated with market betas using the firm's daily stock returns, and the S&P 500 index returns over an estimation window of 120 trading days, starting one day prior to the measurement day [-1; -121].	Firm	Daily	Refinitiv Datastream
Variables of Interest				
CASES	Daily growth rate of the announced cumulative number of confirmed COVID-19-positive cases per million and country.	Country	Daily	European Centre for Disease Prevention and Control (ECDC).
DEATHS	Daily growth rate of the announced deaths associated or caused by COVID-19 per million and country.	Country	Daily	ECDC
EXPOSURE	Weighted country-specific annualized sales revenues [REVENUEi,c,t] with the country´s daily growth rates of COVID-19 cases [CASESc,t], and deaths [DEATHSc,t] per million, respectively. The variable is standardized using z-scores and normalized to a scale from 0 to 100, where higher values indicate a larger firm-specific revenue exposure to COVID-19.	Firm-Country	Daily	ECDC
CONTAINMENT_ CLOSURE	Index measure for the strictness of a country´s COVID-19 policies to contain the spread of the disease. Composing indicators: school closing; workplace closing; cancel public events; restrictions on gatherings; close public transport; stay at home requirements; restrictions on international movement; international travel controls.	Country	Daily	Oxford University´s Government Response Tracker (OxCGRT)
HEALTH_SYSTEM	Index measure for a country´s efforts to strengthen its health systems. Composing indicators: public information campaigns; testing policy; contact tracing; facial covering; vaccination policy; protection of elderly people.	Country	Daily	OxCGRT

ECON_SUPPORT	Index measure for the extent of a country´s economic support. Composing indicators: income support; debt and contract relief.	Country	Daily	OxCGRT
GOV_RESPONSE	Index measure for a country´s summarized countermeasures. All indicators included.	Country	Daily	OxCGRT
Control Variables				
REVENUE	Estimated percentage of revenue a firm derives from an associated country, measured annually. We only include values with a certainty score of 70 or above, as provided by FatSet GeoRev. The certainty score is based on source metadata and ranges from 1 (low certainty) to 80 (declared value).	Firm-Country	Annually	FactSet Revere Geographic Exposure (GeoRev)
VOLATILITY	Stock volatility of daily raw returns.	Firm	Daily	Refinitiv Datastream
FOLLOWING	Natural logarithm of 1 plus the number of analysts following a firm.	Firm	Annually	I/B/E/S
INSTITUTIONAL	Percentage of shares held by institutional investors.	Firm	Annually	I/B/E/S
SIZE	Natural logarithm of 1 plus a firm´s total sales.	Firm	Annually	Refinitiv Datastream
PTB	A firm´s book value per share over its latest closing stock price.	Firm	Daily	Refinitiv Datastream
BOARD	The number of a firm´s board members.	Firm	Quarterly	Refinitiv Datastream
LEVERAGE	A firm´s book value debt over its total assets.	Firm	Yearly	Refinitiv Datastream
ROA	A firm´s operating income before depreciation over total assets.	Firm	Quarterly	Refinitiv Datastream
ESG	Overall firm score based on the self-reported information in the environmental, social, and corporate governance pillars.	Firm	Weekly	Refinitiv Datastream
MEDIA_COVERAGE	Daily percentage of all news agencies in a country that cover the topic of COVID-19.	Country	Daily	Ravenpack Coronavirus Media Monitor
MEDIA_HYPE	Daily percentage of news reports that are covering the topic COVID-19 in a country.	Country	Daily	Ravenpack Coronavirus Media Monitor

MEDIA_SENTIMENT	Daily average level of sentiment that those news reports express towards a firm, that mention both the COVID-19 pandemic and the firm in the report. Measured as the daily average of the difference between the number of positive and negative news reports fulfilling these criteria. A report´s sentiment is determined by systematically matching stories usually categorized by financial experts as having a positive or negative financial or economic impact.	Country	Daily	Ravenpack Coronavirus Media Monitor

Notes: This table provides variable definitions for all variables used in our main regressions.

4 Der Abschlussprüfer als Data Scientist? Über die Chancen und Herausforderungen des Einsatzes von Process Mining in der Wirtschaftsprüfung

4.1 Publication Details

Authors: Lucas Pell, Christian Beer und Christiane Pott

Abstract: Wachsende Datenmengen und neue Berichtspflichten zu nicht-finanziellen Themen erhöhen den Prüfungsumfang. Damit nimmt auch der Kostendruck für zu prüfende Unternehmen zu, wobei an Prüfungsqualität und Prüfungssicherheit ein fortwährend hoher Anspruch bestehen bleibt. Prüfungsleistungen müssen effizienter gestaltet werden, ohne die Grundsätze von Wesentlichkeit und Prüfungsrisiko zu verletzen. Der Berufsstand der Wirtschaftsprüfer muss sich dabei den Herausforderungen der digitalen Transformation stellen. Bereits eine Studie im Jahr 2017 unter 200 CFO, Chief Audit Officers, Mitgliedern des Prüfungsausschusses und weiteren Executives zu künftigen Anforderungen an die Prüfung ergab eindeutige Antworten: Fast 80 Prozent der Befragten erwarteten den Einsatz neuartiger Technologien zur automatisierten Datenanalyse und eine Veränderung des traditionellen Prüfungsprozesses. Sechs Jahre später stehen Technologien zur Verfügung, die das Potential haben, die Effizienz des Prüfungsprozesses zu steigern. Eine dieser Technologien ist das Process Mining mit dem Ansatz, Mandanten perspektivisch einer unterjährigen, kontinuierlichen Prüfung zu unterziehen, tatsächlich stattgefundene Unternehmensprozesse vollständig zu extrahieren, zu analysieren und Abweichungen von der unternehmerischen Prozessplanung offenzulegen. Die Chancen und Herausforderungen sowie die Konsequenzen, die mit einer Integration von Process Mining in den Prüfungsablauf einhergehen würden, werden im Folgenden diskutiert.

Keywords: Process Mining, Big Data, Datenanalyse, Risikoorientierter Prüfungsansatz, Digitale Transformation

Publication Status: Published. WPg – Die Wirtschaftsprüfung, 14(2023), 775-781.

4.2 Einleitung

Die digitale Transformation beeinflusst die betriebliche Wertschöpfungskette von der Logistik über die Produktion, die Buchführung bis hin zum Vertrieb.[20] Innerbetriebliche Abläufe verändern sich häufig durch den Einsatz neuer Technologien.[21] Die Geschwindigkeit, mit der disruptive Innovationen voranschreiten, nimmt zu.[22] Unternehmen implementieren zunehmend Software- und Hardwarelösungen, die auf die Integration von Systemen, Prozessen und Daten abzielen.[23] Als Folge nehmen auch die innerhalb der Unternehmen verarbeiteten und gespeicherten Datenmengen zu.[24] Diese Daten sind keineswegs aufbereitet und auswertbar; Datenvolumina und -struktur erfordern eine wertschöpfende Transformation, die sie als Informationsquelle erst nutzbar macht.[25]

An diesem Punkt setzt Process Mining an, indem es auf historische Daten zugreift und die Visualisierung und Analyse von realen Geschäftsprozessen ermöglicht, wie sie tatsächlich im Unternehmen stattfinden.

Bisher gleicht die konkrete Anwendung von Process Mining in der Wirtschaftsprüfung einer „Black Box“:

- An welcher Stelle kann Process Mining zum Einsatz kommen?
- Welche Voraussetzungen müssen vorliegen?
- Welche normativen Grundlagen gibt es für den Einsatz?
- Welche Ressourcen sind aufzuwenden?
- Wie hat die Dokumentation zu erfolgen?

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20 Vgl. Ziegler u.a., in: Bär u.a. (Hrsg.), Digitalisierung im Spannungsfeld von Politik, Wirtschaft, Wissenschaft und Recht, Berlin/Heidelberg 2018, S. 563–573.

21 Vgl. Bitkom, Big-Data-Technologien, Berlin 2014, S. 17.

22 Vgl. Arbeitskreis Externe und Interne Überwachung der Unternehmung der Schmalenbach-Gesellschaft für Betriebswirtschaft e.V. (AKEIÜ), in: Krause/Pellens (Hrsg.), Betriebswirtschaftliche Implikationen der digitalen Transformation, zfbf-Sonderheft 2018, S. 323.

23 Vgl. Ziegler u.a., a.a.O. (Fn. 2), S. 564–566.

24 Vgl. AKEIÜ, zfbf-Sonderheft 2018, S. 332; Marten u.a., WPg 2020, S. 1331.

25 Vgl. van der Aalst, Process Mining, 2. Aufl., Berlin 2016, S. 3 f.

Unsicherheit und fehlende „Best Practice“ mögen zusätzlich für die Präferenz konventioneller Prüfungsmethoden beim Prüfer sprechen. Eine Diskussion der Einsatzmöglichkeiten und der denkbaren praktischen Anwendung von Process Mining in der Wirtschaftsprüfung samt Analyse der Chancen und Risiken ist indes notwendig. Vor allem sollte Process Mining für eine Anwendung durch den Prüfer regulatorisch eingeordnet werden. Besonders sollte dabei die Rolle des Prüfers in den Fokus rücken: Bedarf es trotz interdisziplinärer Berufsqualifikationen gegebenenfalls einer Vertiefung von Kenntnissen über das Datenmanagement?

4.3 Herausforderungen des Einsatzes automatisierter Datenanalyse

Im Jahr 2015 etablierte der IAASB eine Data Analytics Working Group (DAWG) mit dem Ziel, ihn über technologische Entwicklungen von allgemeinem Interesse zu informieren und Handlungsempfehlungen für den Berufsstand der Wirtschaftsprüfer zu erarbeiten. Bereits in 2016 formulierte die DAWG grundsätzliche Fragen zur Technisierung der Abschlussprüfung mit einem Fokus auf die Herausforderungen einer automatisierten Datenanalysen.[26] Verknüpft mit Ergebnissen aus der Forschung und prüferischen Erfahrungen lassen sich Themenfelder erschließen, die die Implementierung automatisierter Datenanalyse in die Prüfungspraxis potenziell erschweren.

Zunächst setzt die automatisierte Datenanalyse in der Prüfung – ebenso wie die traditionell stichprobenbasierte Prüfung – Datenvollständigkeit, Richtigkeit und Zuverlässigkeit voraus.[27] Die Qualität eines Datenanalyse-Tools basiert auf der Qualität und der Menge der zur Verfügung stehenden Daten.[28] Häufig besteht in Unternehmen nur eine geringe Bereitschaft, Prüfern einen Vollzugriff auf sensible Unternehmensdaten zu gewähren. Auch ist die parallele Nutzung unterschiedlicher Systemanwendungen ein Hemmnis bei der Datenbeschaffung, da Daten dezentral und in unterschiedlichen Formaten gespeichert werden. Die Einsatzbereiche, der Umfang des Einsatzes und die Erfahrung der Mitarbeiter

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26 Vgl. DAWG, Exploring the Growing Use of Technology in the Audit, with a Focus on Data AnalyticsSeptember 2016 (https://www.ifac.org/system/files/publications/files/IAASB-Data-Analytics-WG-Publication-Aug-25-2016-for-comms-9.1.16.pdf ; Abruf: 17.03.2023); in der Folge wurden weitere aufkommende Fragen (FAQ) zu unterschiedlichen Unterthemen veröffentlicht..

27 Vgl. Harder, WPg 2018, S. 1480.

28 Vgl. Gierbl u.a., Expert Focus 2020, S. 612.

mit Systemanwendungen im Unternehmen sind divers. Das erschwert den Austausch zwischen Prüfer und Mitarbeitern des zu prüfenden Unternehmens.[29]

Auch seitens der Prüfungsgesellschaften sind IT-Kenntnisse ein Erfolgsfaktor für den Einsatz automatisierter Datenanalysen. Sie sind eine Voraussetzung für die Beschaffung, Analyse, Aufbereitung und Auswertung von Unternehmensdaten und steigern die Akzeptanz im traditionellen Prüfungsprozess.[30] Die Stärkung der bereits vorhandenen IT-Kenntnisse und die Ausbildung künftiger Prüfer an der Schnittstelle zwischen Prüfung, Naturwissenschaft und Informationstechnologie ist sinnvoll. Viele Prüfungsgesellschaften lassen das im Aufbau interdisziplinärer Teams erkennen. Sie bringen Spezialisten aus der IT, Mathematik, Steuern, Finanzen und der klassischen Prüfung zusammen.[31] Die Folge ist ein hoher Investitions- und Organisationsbedarf. Das betrifft Prüfungsgesellschaften wie Aufsichtsbehörden gleichermaßen.

In der Diskussion stehen auch IT-Sicherheit und Datenschutz. Ein Transfer von Daten zwischen Prüfer und Mandant bietet eine Angriffsfläche für Datendiebstahl, Manipulation und Betrug.[32] Neben der Einrichtung von Sicherheitsbarrieren stehen die Prüfungsgesellschaften damit vor der Herausforderung, Prüfer dafür zu sensibilisieren, angemessen auf planungstechnische und akute Fragen des Datenschutzes und der IT-Sicherheit reagieren zu können.

Tabelle 4.1 fasst die wichtigsten Herausforderungen verschiedener Themenbereiche der Prüfung zusammen und verweist beispielhaft auf grundlegende Standards und Berufsgrundsätze als regulatorischen Rahmen für die Prüfung.

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29 Vgl. Langhein u.a., in: Pflaum/Meinhardt (Hrsg.), Digitale Geschäftsmodelle, Berlin 2019, S. 412.

30 Vgl. Harder, WPg 2018, S. 1480.

31 Siehe beispielhaft PWC, Competence Center – Unterstützung von Wirtschaftsprüfung und Unternehmensberatung (https://karriere.pwc.de; Abruf: 15.03.2023); KPMG, Fokus-Teams (https://kpmg.com; Abruf: 15.03.2023).

32 Vgl. Gierbl u.a., Expert Focus 2020, S. 613.

Tabelle 4.1: Einsatz automatisierter Datenanalysen: Herausforderungen

Thema	Herausforderung	ISA (Beispiele)
Datenerfassung	Daten müssen lückenlos an Abschlussprüfer übermittelt werden und zugleich sicher verwahrt werden. Je nach Umfang stellt auch die Speicherung eine logistische Herausforderung dar.	ISA 220, ISA 230, ISA 300, ISA 500
Kooperation	Mangelnde Erfahrung des Mandanten im Umgang mit IT-gestützten Prüfungen kann die Kooperationsbereitschaft beeinflussen.	ISA 260 (Revised), ISA 315 (Revised)
Datenschutz	Gesetzgebung bezüglich des Datenschutzes und der Speicherung der zu prüfenden Daten ist zu berücksichtigen.	ISQC 1, ISA 720 (Revised), ISA 210
Prüferqualifikation	Die Durchführung der Prüfung mithilfe von Datenanalyse-Tools erfordert spezialisiertes Personal. Es werden vermehrt Prüfer mit mathematischem, Informatik-, naturwissenschaftlichem und technischem Berufshintergrund benötigt.	ISA 200, ISA 220, IESBA Codes of Ethics
Prüferfortbildung	Die Umstellung der Prüfung von der traditionellen Stichprobenprüfung auf eine durch Datenanalyse gestützte Prüfung erfordert ein Investment in die Fortbildung von Abschlussprüfern.	ISA 200, IESBA Codes of Ethics

4.4 Funktionsweise des Process Mining

Voraussetzung für die Anwendung von Process Mining ist ein geeigneter IT-Reifegrad innerhalb des Unternehmens, da verarbeitungsfähige Daten ansonsten nicht, nur lückenhaft oder in nicht ausreichender Qualität und Quantität vorhanden sind. Bei der Analyse von Prozessen im Rahmen des Process Mining wird auf Event Logs zurückgegriffen, die in den ERP-Systemen eines Unternehmens gespeichert werden. Ausgangspunkt für Event Logs sind tatsächliche im Unternehmen durchgeführte Transaktionen (Events). Diese müssen nicht in einem speziellen Format gespeichert werden. Events können sämtliche Aktivitäten umfassen, etwa Nachrichten (Rechnungseingänge), Geldflüsse (Zahlungseingänge) oder Anfragen (Saldenbestätigungen).[33] Möglich wird die Extraktion dieser Informationen mittels digitaler Spuren in Datenbanken und IT-Systemen, in denen die Aktivitäten erfasst werden.[34] Mithilfe von Process-Mining-Tools können zu einem Prozess gehörige Events in der richtigen Reihenfolge erfasst werden, wodurch ein Event Log entsteht.[35] Unstrukturierte, unvollständige und nicht chronologisch erfasste Transaktionen können so aufbereitet werden, dass logische Prozessketten entstehen, die zuvor nicht sichtbar waren. Die Qualität von Event Logs steigt mit der Menge an Daten, die mit den Events abgespeichert werden.[36] Die deskriptiven Informationen über Events, die vom Process-Mining-System analysiert werden und die Auskunft über grundlegende Prozessstrukturen eines Unternehmens geben, werden Meta-Daten genannt.[37] Die wichtigsten Meta-Daten zeigt beispielhaft Tabelle 4.2.[38]

33 Vgl. van der Aalst, International Scholarly Research Notices. S. 5.

34 Vgl. Reinkemeyer, in: Reinkemeyer (Hrsg.), Process Mining in Action: Part 1 – Principles and Value of Process Mining, Berlin 2020, S. 3.

35 Vgl. AKEIÜ, zfbf-Sonderheft 2018, S. 323.

36 Vgl. van der Aalst u.a., a.a.O. (Fn. 15), S. 173.

37 Vgl. Taulli, The Robotic Process Automation Handbook, New York 2020, S. 196.

38 Vgl. Jans u.a., Expert Systems With Applications 2011, S. 33.

Tabelle 4.2: Meta-Daten

Information	**Fragestellung**	**Beispiel**
Case	Zu welchem übergeordneten Prozess gehört die Transaktion?	Purchase Order mit Case-ID 3704
Activity	Welchen Schritt innerhalb des Prozesses bildet die Transaktion ab?	Erstellen einer Bestellung im Rahmen der Purchase Order mit Case-ID 3704
Originator	Wer hat die Transaktion ausgelöst?	Mitarbeiter mit ID 645226, Team 3, Einkauf
Timestamp	Wann wurde die Transaktion erstmals erfasst?	2022-05-21:1145:ECT

Mithilfe von Event Logs können drei Varianten des Process Mining durchgeführt werden:[39]

- Discovery: Allein auf der Grundlage der extrahierten Event Logs wird ein Prozessmodell erstellt.
- Conformance Checking: Event Logs werden mit dem bereits bekannten Prozessmodell des Unternehmens verglichen, um Abweichungen vom Soll-Prozess zu erkennen und ihre Ursachen zu diagnostizieren.
- Enhancement: Event Logs werden mit dem bereits bekannten Prozessmodell des Unternehmens verglichen. Der Unterschied zum Conformance Checking besteht darin, dass das vorgegebene Modell nicht als Soll-Zustand angenommen wird. Anhand der Erkenntnisse aus dem Event Log wird das Modell überarbeitet und ergänzt.

39 Vgl. van der Aalst u.a., a.a.O. (Fn. 15), S. 175.

Ein Abgleich von Event Logs und Prozessmodell wird notwendig, weil die real stattfindenden Prozesse komplexer gestaltet sind, als die linearen Soll-Modelle es vermuten lassen. Process Mining erlaubt, die komplexeren Ist-Prozesse aufzuschlüsseln und somit die einzelnen Schritte und verschiedenen Varianten des Prozesses zu visualisieren. In einer Analyse des Einflusses von Datenvisualisierung auf das Prüferverhalten folgern Ruhnke/Martens: „Erklärende und explorative Visualisierungen werden vor allem in der Prüfungsplanung sowie zur Risikoidentifikation und -beurteilung sowie als Kommunikationsmittel sowohl im Prüfungsteam, in der Prüfungsgesellschaft als auch mit dem Mandanten eingesetzt. Der Einsatz […] kann zu einer effektiven und effizienten Prüfung beitragen.“[40] Erst der Einsatz von Process-Mining-Tools erlaubt eine Visualisierung von Unternehmensprozessen und somit Einblicke in die tatsächliche Prozessstruktur. So entsteht eine prozessuale Abbildung der Unternehmensrealität.[41] Das Prüfungsteam muss sich nicht mehr eigens auf das vorgegebene Soll-Modell verlassen. Das Soll-Modell dient nicht mehr als einzige Beurteilungsrundlage, sondern als Richtlinie zum Abgleich mit dem visualisierten Ist-Modell.[42]

4.5 Process Mining in der Wirtschaftsprüfung

Process Mining kann den traditionellen, risikoorientierten Prüfungsansatz ergänzen. Ohne Process Mining basiert das Vorgehen zur Ermittlung der Prozessstruktur beispielsweise auf stichprobenbasierten Beobachtungen, der Einsichtnahme in Dokumentationen, Interviews mit Mitarbeitern oder Vorkenntnissen über den Prozess. Die Erfassung einer repräsentativen Anzahl an Beobachtungen erfordert einen hohen Zeit- und Ressourcenaufwand. Je nach Qualität der durchgeführten Analyse können Schlussfolgerungen über Prozesse gezogen werden. Doch diese hängen maßgeblich von der Interpretation des Untersuchenden ab. Letztlich entsteht so (nur) eine Skizze der tatsächlichen Vorgänge.[43] Prozesse werden mit zunehmender Digitalisierung nicht durch einen Mitarbeiter, sondern rein automatisch ausgelöst und durchgeführt.[44] Das hat zur Folge, dass Prozessbeteiligte keinen ganzheitlichen Überblick über den tatsächlichen Prozess haben, da Systeme untereinander

40 Ruhnke/Martens, WPg 2020, S. 731.

41 Vgl. Marten u.a., WPg 2020, S. 1331; Reinkemeyer, a.a.O. (Fn. 16), S. 4–7.

42 Vgl. Jans u.a., Expert Systems With Applications 2011, S. 31.

43 Vgl. Reinkemeyer, a.a.O. (Fn. 16), S. 7.

44 Vgl. AKEIÜ, zfbf-Sonderheft 2018, S. 322 f.

kommunizieren und einige Systeme nur Teil-Datenmengen bereitstellen können. So können unbemerkt neue Prozessvarianten entstehen.[45] Die Gesamtheit der Prozesse wird nur noch durch IT-Systeme vollständig erfasst werden können.[46]

4.6 Integration in den Prüfungsablauf – Anwendungsbeispiel IKS-Prüfung

Im Verlauf der Abschlussprüfung wird das Interne Kontrollsystem (IKS) des Unternehmens einer Aufbau- und Funktionsprüfung unterzogen.[47] Dabei wird untersucht, ob die (Kontroll-)Maßnahmen mit dem Ziel, einen ordnungsgemäßen Ablauf des betrieblichen Geschehens zu gewährleisten, zweckmäßig und funktional sind.[48]

Beispiel

Anhand eines fiktiven und vereinfachten Fallbeispiels lässt sich die Integration des Process Mining in die IKS-Prüfung verdeutlichen. Für einen Beschaffungsprozess (Procurement Process) seien folgende Rahmenbedingungen gegeben:

- Das Unternehmen weist einen hohen Digitalisierungsgrad auf und verarbeitet Bestellvorgänge über ein ERP-System.
- Das ERP-System weist eine hohe Kompatibilität mit der verwendeten Process-Mining-Prüfungssoftware des Abschlussprüfers auf.
- Die im ERP-System gespeicherten Daten sind vollständig und verfügen nach ihrer Aufbereitung über die benötigte Qualität.
- Der Beschaffungsprozess findet vollständig innerhalb des Unternehmens statt. Es werden also keine Aktivitäten an externe Dienstleister ausgelagert.
- Durch Rücksprache mit den Prozessverantwortlichen wurde das in Abbildung 4.1 vordefinierte Soll-Prozessmodell „Purchase Order“ erstellt.

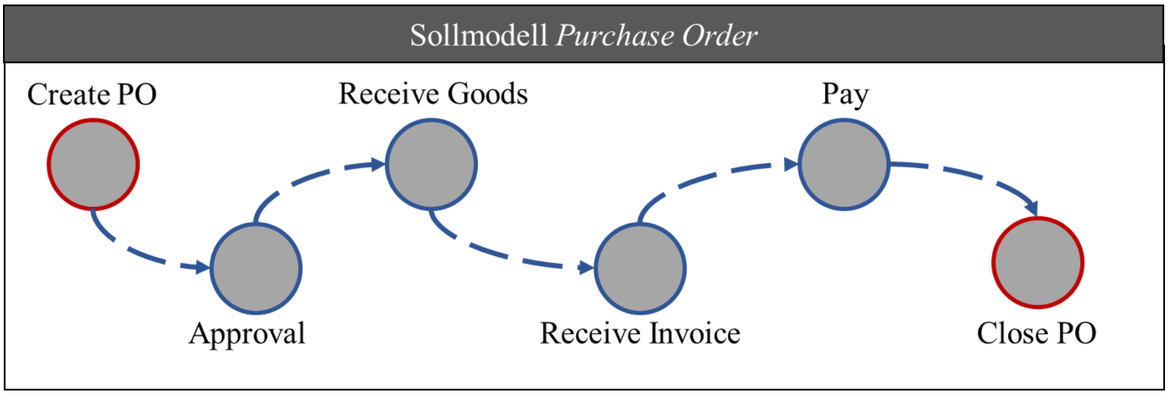
45 Vgl. Reinkemeyer, a.a.O. (Fn. 16), S. 8.

46 Vgl. Wilting, WPg 14/2014, S. I.

47 Vgl. International Standard on Auditing (DE) 315 (Revised): Identifizierung und Beurteilung der Risiken wesentlicher falscher Darstellungen aus dem Verständnis von der Einheit und ihrem Umfeld (ISA [DE] 315 (Revised)), Tz. 12; Marten/Quick/Ruhnke, Wirtschaftsprüfung, 6. Aufl., Stuttgart 2020, S. 397 f.

48 Vgl. ISA [DE] 315 (Revised), Tz. 12.

Abbildung 4.1: Sollmodell Purchase Order



Anhand der definierten Soll-Prozessbestandteile (Activities) können die im ERP-System verfügbaren, unstrukturierten Daten nach Purchase Orders durchsucht werden. Annahmegemäß wird eine Grundgesamtheit von 29.680 Purchase Orders betrachtet. Die definierten Activities werden – angelehnt an den Soll-Prozess – in eine logische Abfolge gebracht. Jeder Prozess wird als Event Log extrahiert. Es wird ein reales Prozessmodell visualisiert. Tabelle 4.3. Tabelle 4.4 zeigt exemplarisch die Struktur eines Event Log auf. Abbildung 4.2 visualisiert das resultierende Prozessmodell.

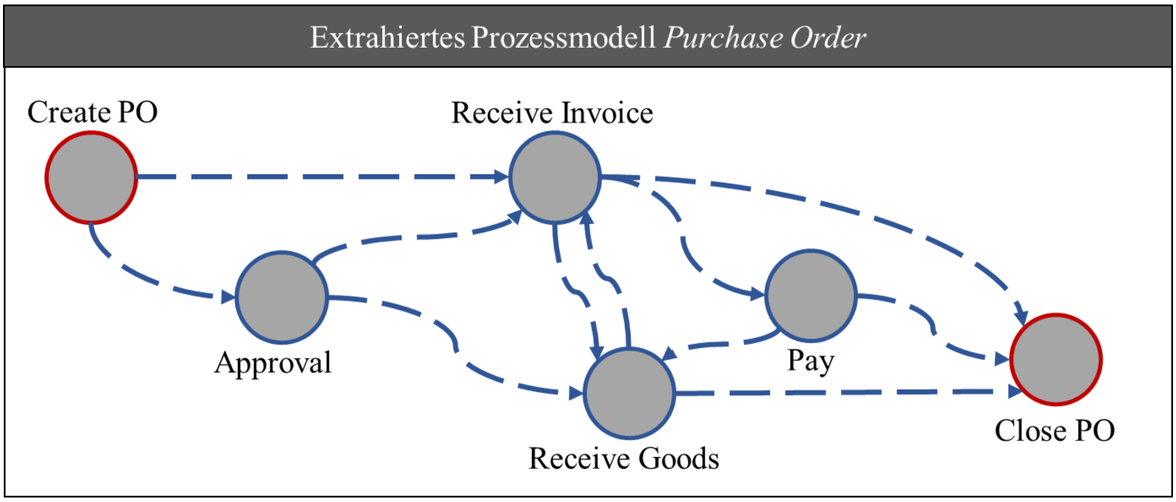
Tabelle 4.3: Struktur eines Event Log (Case ID 462)

Case ID	**Activity**	**Originator**	**Timestamp**
462	Create Purchase Order	Manuela Decker	2022-03-04:1231:ECT
462	Approval	Ben Black	2022-03-04:1402:ECT
462	Receive Goods	ESG GmbH	2022-03-16:1244:ECT
462	Receive Invoice	ESG GmbH	2022-03-17:1021:ECT
462	Pay	Stefan Krug	2022-03-20:1140:ECT
462	Close Purchase Order	Manuela Decker	2022-03-20:1309:ECT

Tabelle 4.4: Detailansicht Prozessstruktur

Detailansicht Prozessstruktur					
Prozessstruktur	**Häufigkeit**		**Durchlaufzeit**		**Prozesswert**
	absolut	Relativ (%)	Durchschnitt	Maximum	Durchschnitt (T€)
1) Create PO-Approval-RG-RI-Pay-Close PO	12.354	41,62	21,93	341	32,567
2) Create PO-Approval-RI-Pay-Close PO	8.958	30,18	32,41	336	34,976
3) Create PO-Approval-RI-Pay-RG-Close PO	3.763	12,68	41,95	269	28,678
4) Create PO-RI-Pay-Close PO	51	0,00	12,72	21	29,567

Abbildung 4.2: Extrahiertes Prozessmodell Purchase Order



Im Rahmen des Conformance Checking werden Soll-Prozess und realer Prozess verglichen. Auf diese Weise können Abweichungen vom Soll-Zustand erkannt und potenzielle Risikopunkte aufgedeckt werden. Die Visualisierung der Modelle zeigt, dass sich das tatsächliche Prozessmodell wesentlich von dem vordefinierten Modell unterscheidet. Es weist eine komplexere Struktur auf und lässt mehrere Prozessvarianten erkennen. Abzulesen ist etwa, dass besonders die Prozessstufen „Receive Invoice", „Receive Goods" und „Pay" in ihrer Reihenfolge variieren. Diese Varianten können mithilfe der Process-Mining-Software und unter Rückgriff auf die extrahierten Event-Logs weiter aufgeschlüsselt werden, um eine Detailansicht freizulegen. Tabelle 4.5 zeigt eine Auswahl der tatsächlichen Prozessabläufe, ihre absoluten und relativen Häufigkeiten und ihre durchschnittlichen und maximalen Durchlaufzeiten.

Tabelle 4.5: Detailansicht der Prozessstruktur

Prozessstruktur	**Häufigkeit**		**Durchlaufzeit**		**Prozesswert**
	Absolut	Relativ	Durchschnitt	Maximum	Durchschnitt (in tausend Euro)
1. Create Purchase Order – Approval – Receive Goods – Receive Invoice – Pay – Close Purchase Order	12.354	41,62 %	21,93	341	32,567
2. Create Purchase Order – Approval – Receive Invoice – Pay – Close Purchase Order	8.958	30,18 %	32,41	336	34,976
3. Create Purchase Order – Approval – Receive Invoice – Pay – Receive Goods – Close Purchase Order	3.763	12,68 %	41,95	269	28,678
4. Create Purchase Order – Receive Invoice – Pay – Close Purchase Order	51	0,00 %	12,72	21	29,567

Prozessstruktur 1

41,62 Prozent der Purchase Orders des Geschäftsjahres folgen dem vordefinierten Sollmodell (Prozessstruktur 1). Bei den restlichen 58,38 Prozent handelt es sich um außerplanmäßige Varianten. Anhand der maximalen Durchlaufzeit können Ausreißer-Prozesse erkannt werden, die weiteren Prüfungshandlungen unterzogen werden sollten. Für eine prüferische Wesentlichkeitseinschätzung wird der durchschnittliche Wert eines Prozesses jeder Prozessvariante berechnet.

Prozessstruktur 2

In Prozessstruktur 2, die über 30 Prozent aller Purchase Orders abbildet, fehlt die Aktivität „Receive Goods". Obwohl eine Abweichung vom Soll-Prozess eindeutig ist, kann nicht zwangsläufig von einem erhöhten Risikopotential ausgegangen werden. Purchase Orders können – neben individuellen Anschaffungen – auch wiederkehrende Zahlungen abbilden, etwa Miet- und Pachtzahlungen, Leasingverträge. Deutlich wird, dass trotz Automatisierung nicht auf das Leitprinzip des prüferischen Ermessens verzichtet werden kann.[49] Process Mining stößt in diesen Fällen an Grenzen. Eine zeitintensive und fachkundige Klärung ist notwendig und ressourcenintensiv.

Prozessstruktur 3

Prozessstruktur 3 enthält zwar sämtliche Prozessstufen des Sollmodells; allerdings fällt auf, dass die eingereichte Rechnung bezahlt wird, *bevor* der Wareneingang erfolgt ist. Das stellt ein finanzielles Risiko dar, das eine weitere Prüfung durch den Abschlussprüfer erfordert. Besonders relevant sind die hohen durchschnittlichen und maximalen Durchlaufzeiten der betroffenen Purchase Orders. Je größer der Zeitraum zwischen „Pay" und „Receive Goods" ist, desto risikoreicher ist die Purchase Order als offene Forderung für das Unternehmen. Bei der weiteren Untersuchung kann der Prüfer erneut auf Process Mining zurückgreifen: Eine Aufschlüsselung der Prozesse nach Originator und Timestamp kann Gründe für die Abweichungen aufdecken.

Prozessstruktur 4

Prozessstruktur 4 stellt mit einer absoluten Häufigkeit von 51 einen Ausnahmefall dar. Hier wird eine Rechnung bezahlt, ohne dass die Purchase Order zuvor genehmigt wurde. Da weniger als ein Prozent aller Purchase Orders betroffen ist, läuft die traditionelle Prüfung Gefahr, diese Prozessvariante – beispielsweise im Rahmen von Mitarbeiter-Interviews und Stichprobenprüfungen – nicht zu erkennen.

Zwischenergebnis

49 Vgl. Downar/Fischer, in: Obermaier (Hrsg.), Handbuch Industrie 4.0 und Digitale Transformation, Wiesbaden 2019, S. 774.

Dieses Anwendungsbeispiel macht die Stärken und Schwächen des Process Mining in Ansätzen deutlich. Auf der einen Seite kann die Grundgesamtheit der Transaktionen eines Geschäftsjahres untersucht werden; einzelne Sachverhalte können beleuchtet oder Ausreißer identifiziert werden. Da die Meta-Daten automatisch und unabhängig von den bearbeitenden Mitarbeitern des Unternehmens gespeichert werden, entsteht eine Abbildung der Unternehmensrealität.[50] Die dynamische Visualisierung von Prozessstrukturen durch geeignete Process-Mining-Software erlaubt Abschlussprüfern, einen Überblick über die Beziehungen von Unternehmenstransaktionen untereinander zu gewinnen.[51] Auf der anderen Seite kann Process Mining den Prüfungsablauf lediglich unterstützen. Mögliche prozessuale Problemstellen werden zwar aufgezeigt, müssen jedoch im Rahmen des Prüfungsrisikomodells untersucht, bewertet und begründet werden. Aufbereitete Unternehmensdaten bedürfen weiterhin eines hohen Maßes an Interpretation, prüferischem Ermessen, Branchen- und Unternehmenskenntnis sowie prüferischer Erfahrung.

4.7 Fazit

Process Mining kann als Baustein der Prüfung dabei unterstützen, ein klareres Bild von Geschäftsprozessen, ihren Charakteristika und Schwächen zu zeichnen. Unrichtigkeiten im Prozessablauf können aufgedeckt und Einzelfallprüfungshandlungen auf dieser Basis gezielt ausgedehnt werden.[52] Process Mining kann ergänzend in Unternehmen zum Einsatz kommen, die über eine adäquate Systeminfrastruktur verfügen. Angepasste Aus- und Fortbildungskonzepte, die eine Schnittstelle prüferischer Kompetenz mit IT-Fachkenntnissen anstreben, können die Integration von Process Mining in den Prüfungsprozess vereinfachen und einen Einsatz dort ermöglichen, wo er prüferisch sinnvoll ist.[53]

Noch stehen zahlreiche Herausforderungen einer flächendeckenderen Anwendung entgegen. Unternehmen müssen einen hohen IT-Reifegrad aufweisen und Daten müssen vollständig und konsistent beschaffbar sein. Der Bedarf an Datensicherheit in der Prüfung steigt. Die

50 Vgl. Jans u.a., in: Halpin u.a. (Hrsg.), Enterprise, Business-Process and Information Systems Modeling, Berlin/Heidelberg 2011, S. 4 f.

51 Vgl. DAWG, a.a.O. (Fn. 8), S. 7.

52 Vgl. *IDW Prüfungsstandard: Zur Aufdeckung von Unregelmäßigkeiten im Rahmen der Abschlussprüfung (IDW PS 210)* , Tz. 58f. (Stand: 12.12.2012).

53 Vgl. Werner u.a., International Journal of Accounting Information Systems 2021, S. 2.

Kooperation von Unternehmen ist Voraussetzung. In naher Zukunft zeichnet sich kein Bild einer automatisierten Prüfung *durch* Process Mining ab. Vielmehr werden Prüfer zu „Data Scientists", die *mit* Process Mining eines von mehreren verfügbaren Tools zur Steigerung von Prüfungseffizienz und -qualität einsetzen könnten. Traditionelle Prüfungsansetze müssen ihre Gültigkeit behalten.[54] Prüferische Weitsicht, Interpretation, Ermessensspielräume und Menschenkenntnis werden insoweit weiterhin einen Grundpfeiler des Prüfungswesens bilden.

Auch der IAASB fördert den Erhalt des Status Quos, und zwar insofern, als er keine grundlegende oder rasche Überarbeitung der ISA vorsieht.[55] In einer Abfrage aus dem Jahre 2016 betont er dennoch die Notwendigkeit einer Anpassung der ISA an die digitale Transformation.[56] Einen Schritt weiter ist das US-amerikanische AICPA: In dessen überarbeiteten Standard „Audit Evidence" werden erstmals konkrete Anwendungsmöglichkeiten für Process Mining genannt.[57] Offen ist, inwieweit sich Erkenntnisse aus der praktischen Anwendung dieses Standards auf die ISA übertragen lassen werden.

54 Vgl. Harder, WPg 2018, S. 1480.

55 Vgl. DAWG, a.a.O. (Fn. 8), S. 9–11.

56 Vgl. DAWG, a.a.O. (Fn. 8), S. 19

57 AU-C Section 500: Audit Evidence.

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