Corporate Tax Avoidance and Social (Ir-)Responsibility: Essays on the Market Implications and the Role of Media Attention

Dissertation
zur Erlangung des Doktorgrades
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Eberhard Karls Universität Tübingen

vorgelegt von

David Gremminger

aus Buchen (Odenwald)

Tübingen

2023

Tag der mündlichen Prüfung:	**22. September 2023**
Dekan:	**Prof. Dr. Ansgar Thiel**
1. Gutachter:	**Prof. Dr. Dominik Papies**
2. Gutachter:	**Prof. Dr. Martin Ruf**

Danksagung

Als ich 2012 meine akademische Laufbahn in Tübingen begann, wusste ich allenfalls in sehr groben Zügen, was es bedeutet, zu promovieren. Nicht im Entferntesten hätte ich zu diesem Zeitpunkt daran gedacht, einmal selbst diesen Weg einzuschlagen. Somit ist es für mich alles andere als selbstverständlich, heute, 11 Jahre später, meine Dissertation fertigzustellen. Dass es dazu kommen konnte, ist der Verdienst unzähliger Menschen, die mich auf diesem Weg begleitet und unterstützt haben. Ihnen gebührt mein tiefer Dank und einige davon möchte ich stellvertretend namentlich erwähnen.

Zuallererst möchte ich meiner Familie danken, allen voran meinen Eltern. Sie haben mich in jeder Phase meines Lebens bedingungslos unterstützt und es mir damit ermöglicht, heute der zu sein, der ich bin. Vieles davon war und ist nicht selbstverständlich und hierfür bin ich zutiefst dankbar. Ebenso dankbar bin ich der Familie meiner Freundin (und bald Ehefrau) Sophia, die nach den vielen gemeinsamen Jahre auch meine eigene ist. Zu gerne hätte ich auch mit Theo auf die Abgabe meiner Dissertation angestoßen.

Nichts geht ohne gute Freundinnen und Freunde, die immer offene Ohren für Sorgen und Nöte haben – sei es in Bezug auf die Promotion oder auf andere Dinge. Unter den vielen Menschen, die ich zu meinem Freundeskreis zählen darf, möchte ich stellvertretend für alle im Besonderen Luisa, Philipp, Sarah und Sebi nennen. Ich kann mich glücklich schätzen, Euch als Ratgeber und Vertrauenspersonen an meiner Seite zu wissen.

Auch wenn diese Dissertation am Ende des Tages das Ergebnis meiner eigenständigen Arbeit ist, habe ich über die letzten Jahre dennoch gelernt, dass der Weg zur Promotion ein Teamprojekt ist. Ich danke meinen tollen Kolleginnen und Kollegen für den regelmäßigen fachlichen Austausch über Ideen, die noch nicht ganz zu Ende gedacht sind, für die Durchhalteparolen in Phasen des gefühlten Stillstands und nicht zuletzt auch für Kaffeepausen und das gemeinsame Feierabendbier. All das trug zu einer guten und produktiven Atmosphäre bei und dazu, dass ich jeden Tag gerne ins Büro gekommen bin. Namentlich nennen will ich dabei insbesondere Alexandra Becker, Georg Thunecke, Leonie Raiser, Monika Burkhardt und Stefan Mayer, sowie allen voran Daniela Mast und Jonathan Fuhr, die meine Zeit an der Universität in besonderer Weise geprägt haben. Dankend erwähnen will ich auch Samuel Stäbler, der als Koautor einen wertvollen Beitrag zur Erstellung von Kapitel 2 dieser Dissertation beigetragen hat sowie Prof. Dr. Martin Ruf, der ohne zu zögern einwilligte, die Zweitbetreuung meiner Dissertation zu übernehmen.

Ganz besonders aber gebührt meine Dankbarkeit Prof. Dr. Dominik Papies, der als mein Doktorvater, Betreuer, Ratgeber, Koautor, Chef und Kollege die Person ist, die auf meinem bisherigen professionellen Werdegang die wohl größten Spuren hinterlassen hat. Schon während Bachelorstudiums begann ich meine Arbeit am Lehrstuhl und es war Dominiks Zutrauen in meine Fähigkeiten, das maßgeblich zu meiner Entscheidung beigetragen hat, den Weg der Promotion zu beschreiten. Ich danke Dir für unser zu jeder Zeit harmonisches Arbeits- und Betreuungsverhältnis, für die vielen Gespräche auf Augenhöhe und für die ansteckende Begeisterung, mit der Du Dich mit Fragen der Forschung und weit darüber hinaus beschäftigst. Ich werde unsere Zusammenarbeit in bester Erinnerung halten – oder um es in Deinen Worten auszudrücken: Es war nicht alles schlecht.

Zu guter Letzt danke ich meiner besten Freundin, Ansprechpartnerin in allen Lebenslagen sowie zukünftigen Ehefrau Sophia. Ich bin unendlich dankbar dafür, dass wir gemeinsam schon eine so lange und eregnisreiche Zeit verbringen durften, dass wir so viele schöne Erinnerungen teilen und dass Du immer für mich da bist und mich unterstützt. Ich bin unbeschreiblich froh darüber, mich immer auf Dich und Deine Unterstützung verlassen zu können.

Und liebe Oma Else: Ich darf Dich beruhigen, ich habe jetzt erstmal genug von der Studiererei. Ab jetzt schaff' ich "richtig"!

Zusammenfassung

In den vergangenen Jahren haben Firmen ihr Engagement im Bereich der sozialen Unternehmensverantwortung ("corporate social responsibility"; kurz: CSR) verstärkt hervorgehoben. Angesichts dieser Entwicklung ist es bemerkenswert, dass gleichzeitig große Unternehmen, auch solche, die sich sonst als besonders sozial verantwortlich darstellen, vermehrt in Medienberichte über Steuervermeidung verwickelt waren. Dies stellt einen Widerspruch dar und wirft mehrere Fragen auf, die in dieser Dissertation behandelt werden sollen. Zu diesem Zweck untersucht diese Arbeit Auswirkungen des Steuerverhaltens von Unternehmen sowie die Konsequenzen von gesellschaftlich (un-)verantwortlichem unternehmerischem Handeln. Ein besonderer Fokus liegt dabei auf der Rolle der Medienberichterstattung. Der erste Aufsatz (Kapitel 2) kommt zu dem Ergebnis, dass die Medienberichterstattung über das Steuerverhalten zwar keinen Einfluss auf abnormale Aktienrenditen hat, die Verbraucher es jedoch wahrnehmen und negativ bewerten, wenn die kritische Medienberichterstattung über Steuervermeidung zunimmt. Darüber hinaus steigt das Handelsvolumen in Folge verstärkter negativer Berichterstattung, was auf heterogene Reaktionen der Anleger schließen lässt. Der zweite Aufsatz (Kapitel 3) zeigt, dass die Zahlung eines höheren Steuersatzes (d.h. der Verzicht auf aggressive Steuervermeidung) dazu beitragen kann, die negativen Auswirkungen von sozial unverantwortlichem Verhalten in anderen Bereichen auf den Unternehmenserfolg abzuschwächen. Die dritte Arbeit (Kapitel 4) zeigt das Potenzial moderner "Topic Modeling"-Techniken auf, indem sie die Medienberichterstattung über das Steuerverhalten von Unternehmen und die Bedeutung der Berichterstattung über Steuervermeidung im Vergleich zu anderen steuerbezogenen Nachrichten untersucht. Insgesamt trägt diese Dissertation zum Verständnis der komplexen Zusammenhänge zwischen dem Verhalten von Unternehmen und seinen Folgen bei und verdeutlicht, wie wichtig es ist, die Perspektiven der verschiedenen Interessengruppen zu berücksichtigen. Auf diese Weise kann die Arbeit hoffentlich den öffentlichen Diskurs darüber beeinflussen, wie der Steuervermeidung von Unternehmen angemessen entgegnet werden kann.

Synopsis

In recent years, companies have increasingly emphasized their commitment in the area of corporate social responsibility (CSR). In view of this development, it is striking that at the same time, large corporations, including some that otherwise portray themselves as particularly socially responsible, are caught evading taxes. This poses a conundrum and raises several questions that this dissertation aims to address. To this end, this thesis explores the effects of corporate tax behavior and consequences of socially (ir-)responsible behavior. A particular focus is on the role of media coverage in this context. The first paper (Chapter 2) finds that while media coverage of tax behavior does not affect abnormal stock returns, consumers notice and penalize brands that engage in tax avoidance, and trading activity increases in response to media coverage of tax avoidance, suggesting heterogeneous reactions across investors. The second paper (Chapter 3) shows that paying a higher tax rate can help mitigate the negative effects of socially irresponsible behavior on firm performance. The third paper (Chapter 4) demonstrates the potential of state-of-the-art topic modeling techniques by examining the media coverage of corporate tax behavior and the importance of tax avoidance reporting relative to other tax-related news. Overall, this thesis contributes to our understanding of the complex relationships between corporate behavior and its consequences, highlighting the importance of considering the perspectives of multiple stakeholders. In doing so, the thesis can hopefully inform the public discourse on how to adequately address the issue of corporate tax avoidance.

Contents

List of Figures

List of Tables

1 Introduction

"The social responsibility of business is to increase its profits" is the title and pointed summary of a seminal essay by Milton Friedman (1970), which became known as the Friedman doctrine and which significantly impacted entrepreneurial activities in the following decades. The essay advocated the so-called *shareholder primacy* and argued that there was no such thing as a "social responsibility" for managers beyond maximizing shareholder value. The essence of Friedman's argumentation was that, as the agent of the owners of a public corporation, the only responsibility of managers is to their shareholders. Ever since, scholars and practitioners have debated whether or not public companies and their management should also engage in activities that serve the interests of stakeholders other than shareholders. These types of corporate activities, i.e., activities in which profits are potentially sacrificed to pursue a social goal, fall within the scope of so-called *corporate social responsibility* or, in short, CSR (Bénabou and Tirole, 2010). Friedman's reasoning implies that managers can only take CSR actions if they also increase the shareholder value of the company, and that management decisions that contradict this principle constitute a breach of trust with the owners (Friedman, 1970).

Although Friedman's work significantly impacted much of the corporate world of the late twentieth century and laid the foundation for the *shareholder theory*, his perspective was and still is far from uncontroversial, as can be seen for example in comments of Friedman's Nobel Prize-winning colleagues Joseph Stiglitz and Oliver Hart who have taken a clear position against his theory of shareholder primacy (Hart and Zingales, 2017; Sorkin, 2020; Stiglitz, 2015). Recurring elements of the critique include that short-term maximization of profits typically comes at the expense of long-term value generation, and that it creates incentives for managers to prioritize myopic investments over those that potentially yield larger returns in the longer run (e.g., Stiglitz, 2015; Stout, 2013). Some argue that the sole focus on profit maximization encourages managers' opportunistic behaviour as it can help them achieve short-term financial goals (e.g., Hart and Zingales, 2017). For example, managers may decide to cut or at least minimize expenses for salaries, research and development, or customer relationship management, which may increase share prices in the short-run, while being at the expense of other non-shareholder stakeholders and of potential future returns on investment (Stout, 2013).

Despite constant and increasingly vocal criticism, it took until 2019 that the *Business Roundtable* (BRT), a lobbyist alliance of around 200 influential CEOs from major US corporations, including the likes of Sundar Pichai (*Alphabet*), Jeff Bezos (*Amazon.com*), and Kevin Johnson (*Starbucks*), collectively turned their backs on shareholder primacy. In their joint statement, they redefined their understanding of the purpose of a corporation, which long has been the maximization of shareholder value, and which the alliance reformulated to now also consider the interests of other stakeholders (Business Roundtable, 2019). The statement, which received a great deal of attention by policymakers and the broader public (e.g., Gelles and Yaffe-Bellany, 2019; Harrison, Phillips, and Freeman, 2020; Newmyer, 2020), can be understood as a clear commitment to the social responsibility of a business and it reflects the increasing importance that companies have attached to CSR activities over the years. In fact, the trend towards more deliberate engagement with stakeholders other than investors was emerging even before the release of the BRT statement. For example, of the 250 largest companies worldwide, more than 90 percent published a CSR report in 2015, while in 2005, only 64 percent produced such a report (Meier and Cassar, 2018). What is more, estimates indicate that the Fortune Global 500 companies spent approximately $20 billion annually on CSR activities in the years from 2013 to 2015 (EPG Economic and Strategy Consulting, 2015).

This seemingly increasing focus of large companies on the impact of their business on society contrasts with another observation that can be made over the years, and that seems to be at odds with the commitment to CSR, as communicated in the BRT statement: There have been more and more media reports of aggressive tax avoidance by large corporations since the early 2000s, and it has become a common theme in the public debate that firms do not pay their "fair share" in contributing to the well-being of society (Schoen, 2014). To put the $20 billion in annual CSR spending by Fortune Global 500 companies in perspective, the *Tax Justice Network*, an independent advocacy group of researchers that advises policymakers, estimates the global financial damage caused annually by tax abuse of multinational corporations is $312 billion (Tax Justice Network, 2021).

Tax payments are crucial for the functioning of society, as they represent the major source of government revenues and thus serve to finance public sector expenditures. A significant portion of tax revenue is generated by businesses.[1] Tax money allows a state to fulfill its purpose, namely to ensure public order and safety and to protect the rights and freedoms of its citizens. In other words, by paying taxes, companies can contribute to the well-being of societies in which they operate, and this description closely matches the definition of CSR given above. In fact, the public goods in which a welfare state invests tax money are very similar to those in which com-

[1]For example, for the composition of the budget of the Federal Republic of Germany, see https://www.bundeshaushalt.de/DE/Bundeshaushalt-digital/bundeshaushalt-digital.html (last access: April 01, 2023)

panies invest their CSR budgets: for example, in education, research, health, or environmental protection, to name just a few (Davis et al., 2016). Therefore, tax avoidance and CSR are closely linked, in that refraining from tax avoidance can also be seen as delegating CSR activity to the state (Wagner, 2018). If paying taxes benefits society, avoiding taxes is consequently detrimental, since it deprives the state of financial resources that it could otherwise invest in the welfare of society. One could counter that it is possible that, similar to a make-or-buy decision, companies might fully use all of the savings made through tax avoidance to invest in own CSR initiatives. However, given the previously mentioned discrepancy between the CSR spendings made ($20 billion per year for the Fortune Global 500 according to EPG Economic and Strategy Consulting (2015)) and the savings of a reduced tax burden through tax avoidance ($312 billion per year for all multinational firms according to Tax Justice Network (2021)), this seems rather unlikely. On top of that, it is not clear if companies allocate their CSR spendings in a purely philanthropic way. It is also conceivable that companies primarily support high-visibility projects that optimize the company's image, not necessarily the common good. Consequently, tax avoidance can be considered an act of *corporate social irresponsibility* (CSI) as defined by Strike, Gao, and Bansal (2006) as corporate behavior that "negatively affects an identifiable social stakeholder's legitimate claims", i.e., tax avoidance reduces the amount of money that a state has at its disposal and that society thus receives indirectly from companies in the form of public goods.

Policymakers have not been inactive and have put the fight against corporate tax avoidance on the agenda at all administrative levels. First, there is the initiative for a global minimum tax rate, which 130 countries worldwide agreed on in 2021 under the leadership of the OECD (OECD, 2021). Also in 2021, the European Union adopted a country-by-country reporting legislation that is supposed to increase tax transparency by requiring multinational firms to reveal their tax payments in all countries in which the they operate, including low-tax countries (European Commission, 2021). In addition to these larger-scale initiatives, there are also several attempts to curb tax avoidance on national levels (e.g., see Dwenger and Treber, 2022; Dyreng, Hoopes, and Wilde, 2016). In summary, policymakers seem to have a strong interest in countering tax avoidance, and it is important to understand how well different measures work.

While companies readily report positive CSR news themselves because they expect positive reactions from customers, investors, and employees, the opposite is the case for CSI incidents (Stäbler and Fischer, 2020). In order for the public to become aware of corporate misbehavior such as the involvement in a tax avoidance scandal or in other types of CSI incidents, the media are essential in their function as a control authority (Kovach and Rosenstiel, 2021). An important function of the news media is to act as "watchdogs" (Hachten, 1963, p. 13), i.e., to monitor areas of the society that would otherwise be unseen to the broader public. This includes government actions, but it also extends to the activities of other powerful institutions such as corporations. Many CSI incidents would never have caught the public's attention if it were not for investigative journalists (Stäbler and Fischer, 2020). Consider for example recurring news reports in various news outlets about poor working conditions of employees at *Amazon.com* logistics centers (Leonhardt, 2021), the revelation of *Facebook*'s Cambridge Analytica data privacy scandal through *The New York Times* and *The Guardian* (Cadwalladr, 2018), and not least the investigation of major tax data leaks through the *International Consortium of Investigative Journalists* (ICIJ) in the in the *LuxLeaks* (ICIJ, 2014) and the *Paradise Papers* (ICIJ, 2017). The mere fact that corporate misconduct becomes known to the public creates the possibility of eventually evoking a reaction among consumers and investors. This underscores the central role that the media play in reducing the information asymmetry between firms and the public and it is an open question how the media fulfill this role in the context of corporate tax behavior.

The above observations create tension around the issues of tax avoidance, CSR, CSI, and their coverage in the media. Especially the discrepancy between firms' high-visibility CSR actions on the one hand and their aggressive tax policies at the expense of society on the other poses a conundrum and raises questions: How do consumers assess corporate actions in the fields of CSR and (the avoidance of) tax payments? How do investors react to news about corporate tax avoidance? Does refraining from aggressive tax avoidance have the same firm performance implications as engagement in CSR? Do one effect depend on the other? What role do the media play in disseminating information about corporate actions? And which policy measures are likely to be successful in curbing corporate tax avoidance? This thesis sets out to shed light on these issues and it aims to contribute to finding appropriate answers.

In doing so, the dissertation ties in with existing literature in several ways. First of all, it adds to the emerging strand of research about corporate sociopolitical activism. Recent literature shows that it becomes increasingly relevant for customers that firms behave in a way that conforms with their values (Nickerson et al., 2022). Therefore, more and more firms are taking a clear stance regarding often controversial sociopolitical questions (e.g., Eilert and Nappier Cherup, 2020). This sociopolitical activism can have either favorable or adverse implications for stakeholder relationships and on firm value, depending on how strongly the firm's position deviates from the values of key stakeholders (e.g., Bhagwat et al., 2020; Hambrick and Wowak, 2021). This literature has so far neglected the area of tax payments, tax avoidance, and their respective market implications, and I intend to fill this void. Moreover, I would like to explore the issue of tax avoidance from a marketing perspective. Previous literature has investigated the effects of corporate tax avoidance, yet mostly from an accounting perspective. That is, research has attempted to measure the actual degree of tax avoidance as precisely as possible, e.g., based on accounting-based proxies (e.g., Desai and Dharmapala, 2009; Gallemore, Maydew, and Thornock, 2014; Hanlon and Slemrod, 2009). These studies are valuable contributions to the literature since they quantify the direct financial implications of tax avoidance, but they offer limited insight in terms of other stakeholders' perceptions of a firm's tax behavior, for example consumers or the media. Therefore, this dissertation pays special attention to *media coverage* of tax behavior to measure not only the actual degree of tax aggressiveness, but also the extent to which the broader public is aware of and reacts to it. In this thesis, I show that changes to the public awareness of a company's tax avoidance activity can actually be harmful to its brand image.

Following the general introduction (Chapter 1), this dissertation thesis entails three essays that I present in Chapters 2 to 4. Chapter 5 concludes the thesis by integrating the findings of the individual projects into a joint discussion. All three essays examine the issue of corporate tax avoidance as a form of socially irresponsible corporate behavior from different angles. As a whole, the thesis intends to give the reader multi-faceted insights into the market implications of media attention to tax-issues, into the interplay between tax avoidance and other types of CSI, and into the role of the news media in making tax-related corporate actions public. I integrate the three essays into one framework in Figure 1.1.

Chapter 2 is joint work with Dominik Papies (University of Tübingen) and Samuel Stäbler (Tilburg University), and the article presented there is titled *"Corporate Tax Avoidance in the Spotlight – How its (Social) Media Coverage Affects Firm Value, Brand Metrics, and Trading Volume"*. The project addresses the question how different actors in the market react to unanticipated changes in the volume and valence of media attention to tax-related information in traditional and social media. Specifically, we want to understand how investors and consumers respond to tax-related news in the media. To this end, we assemble and analyze a comprehensive data set consisting of close to 35,000 news articles, over 9 million postings on the microblogging site

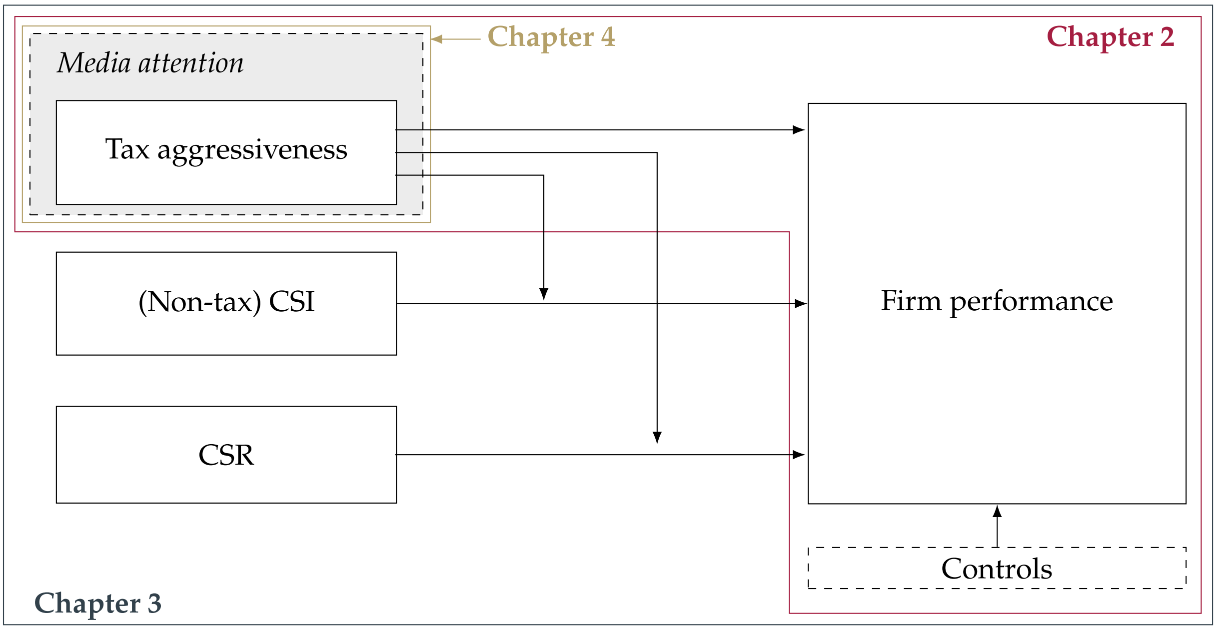


Figure 1.1: Conceptual framework of the thesis and its chapters

Twitter, brand reputation measures from the market research company YouGov, as well as corresponding accounting and stock market data for the 500 largest US firms over a period of 10 years. The red box in Figure 1.1 depicts the scope of Chapter 2 within the dissertation thesis. We do not find evidence in our analyses for stock prices to drop following an increase in the volume or negativity of tax-related media attention. For consumer-based brand metrics, however, we do find a significant effect of media attention. This implies that consumers seem to care about tax media attention, but this does not translate into reduced market value for a firm. An important policy implication that we draw from this finding is that public awareness of corporate tax avoidance does not appear to be what is lacking to fight corporate tax avoidance. To effectively curb tax avoidance, policies aimed solely at increasing tax transparency (such as the EU country-by-country-reporting directive) are therefore unlikely to change firms' tax behavior, since firms do not seem to fear direct financial losses in the form of lower market value due to increased consumer awareness.

Chapter 3, titled *"Paying Taxes to Calm Tempers? The Moderating Role of Effective Tax Rates on Value Implications of Corporate Misdeeds"* is a single-authored research project. The essay embeds the concept of tax payments in the broader field of corporate social (ir-)responsibility, as illustrated by the large grey box in Figure 1.1. In this study, I examine the interplay between the degree of a firm's tax aggressiveness and its CSI incidents with respect to their firm value implications. The essay aims to answer the question whether refraining from aggressive tax avoidance can alleviate consequences of other (non-tax) CSI incidents. For this purpose, I extend the data set used in Chapter 2 with another data source, namely the *MSCI ESG Ratings* data set (formerly known as *KLD Stats* database) that provides third-party measures of firms' CSR and CSI activities. By studying the moderating effect of a firms' effective tax rates in the relation between CSI incidents and firm performance, I find evidence that tax payments can mitigate the negative consequences of corporate social irresponsibility in non-tax areas. My research shows that the individual components of the multi-layered constructs of CSR and CSI can have a different impact on firm performance, and breaking them down into their constituent parts can help to understand the interplay between them.

In Chapter 4, I present another single-authored article which is titled *"Exploring the Discourse of Corporate Taxes: A BERTopic Analysis of Tax-Related Firm Media Coverage"*. The article looks more deeply into what exactly newspapers talk about when they report about firms in a tax context (illustrated by the golden box in Figure 1.1). It is insightful to better understand the content of firm news coverage in the area of taxes, as this can give a sense of how the media carry out their watchdog role when it comes to tax-related corporate activities. I use the corpus of about 35,000 newspaper articles from Chapter 2 as a basis for my largely descriptive analyses. To identify the topics articles covered by these articles, I employ *BERTopic* (Grootendorst, 2022), a state-of-the-art neural topic modeling technique. In investigating the content of the articles, I provide relevant insights regarding which issues newspapers report when they mention corporations in a tax context, how tax-related topics in firm media coverage emerge and fade over time, and how it differs between news outlets. Beyond these substantive findings, the study also demonstrates the potential of novel methods from computer linguistics for research in the field of firm media coverage and it outlines potential use cases of BERTopic along the research pipeline.

All in all, I hope that my thesis provides a comprehensive view on the issue of tax avoidance from various perspectives. The results and the answers offered by this dissertation thesis are potentially relevant to a broad set of stakeholders including policymakers, researchers, managers, and society at large. I therefore hope that my research will constitute a valuable addition to the existing literature.

2

Corporate Tax Avoidance in the Spotlight – How its (Social) Media Coverage Affects Firm Value, Brand Metrics, and Trading Volume

David Gremminger, Samuel Stäbler, & Dominik Papies

Statement of contribution

Chapter 2 presents a slightly modified version of the working paper "Corporate Tax Avoidance in the Spotlight – How its (Social) Media Coverage Affects Firm Value, Brand Metrics, and Trading Volume" (in earlier stages titled "Do Consumers and Investors Care About Corporate Tax Avoidance? Understanding the Role of (Social) Media") by David Gremminger, Samuel Stäbler (Tilburg University), and Dominik Papies (University of Tübingen). The contributions of the authors are as follows: David Gremminger conducted all data collection, management, main analyses, and drafted the first version of the working paper. Samuel Stäbler contributed post-hoc analyses and discussion regarding consumer-based firm metrics, and edited and revised the manuscript. Dominik Papies gave the initial idea for the study, supervised the entire research project, gave feedback, and edited and revised the manuscript. The working paper is currently in preparation for submission.

Acknowledgements: The authors thank Simone Wies, Harald van Heerde, Frank Germann, and Marc Fischer for their excellent feedback, which helped move the project forward. Further, they acknowledge all participants of the European Marketing Academy Conference 2021 in Madrid (Spain) and the SALTY Quantitative Marketing Conference 2022 in Düsseldorf (Germany) for their helpful comments. The authors also acknowledge support by the state of Baden-Württemberg through bwHPC.

Abstract

Public interest in tax avoidance activities of large multinational corporations has been growing, with media playing a pivotal role in informing the public. The firm value implications for tax-avoiding firms, however, are unclear. While firms benefit because cutting taxes reduces costs, brand equity may suffer if consumers disapprove of tax-avoiding brands. The net effect and the role of (social) media's attention in shaping consumers' and investors' behavior are not well understood. To address this void, we analyze close to 500 of the largest US firms across 10 years and measure their tax payments, stock market performance, and the media coverage of their tax behavior. In contrast to expectations, we do not find evidence that media coverage of tax avoidance affects abnormal returns, i.e., investors do not seem to penalize firms for public coverage of tax avoidance. Our post-hoc analyses reveal that consumers notice corporate tax avoidance and brand strength suffers. In addition, trading activity increases in response to media coverage of tax avoidance. This suggests that media attention to tax avoidance matters to consumers and investors, but that investors are heterogeneous in their assessment of this information.

2.1 Introduction

In the past decade, corporate tax avoidance has been subject to growing public scrutiny. Not only since the *International Consortium of Investigative Journalists* (ICIJ) published their findings from the analyses of major tax data leaks in the *LuxLeaks* (2014) and *Paradise Papers* (2017), corporate tax avoidance has been the topic of many articles by leading news outlets. In many cases, these articles reveal information that has not been previously known to a broader audience, e.g., in 2021 *The New York Times* published an article that contained a list of more than 20 profitable US firms that reported effective tax rates below zero over the previous three years (Cohen, 2021). The attention that the popular press dedicates to this issue has drawn the public's interest, created an increased awareness, and fueled a public debate. A 2014 CNBC survey indicates that 62 percent of the population in developed countries thinks that companies do not pay their "fair share" (Schoen, 2014). One example is the case of Starbucks in the UK. In October 2012, following an investigation by *Reuters*, the US coffeehouse chain was heavily criticized for paying as little as £8.6 million in taxes between 1998 and 2012, while reporting about £3 billion in UK sales (i.e., Starbucks paid about 0.3 percent taxes on its reported sales). Although apparently legal, this aggressive tax avoidance behavior was described as being "extremely unfair" and "disgraceful" by politicians (Bergin, 2012). Disgruntled consumers used social media platforms such as Twitter to call for boycotts and, by this, put further pressure on Starbucks (Thompson and Houlder, 2012). In December 2012, Kris Engskov, then managing director of Starbucks UK, announced that Starbucks would pay an additional £20 million to the UK tax authorities. Another more recent example occurred during the COVID pandemic when there was a public debate about whether firms who are under financial pressure due to the pandemic are eligible for bailouts financed with taxpayers' money when they engage in aggressive tax avoidance (Financial Times Editorial Board, 2020).

These observations raise the question of whether and to what extent a firm's tax conduct affects brand equity, and more specifically, how consumers and investors react to the media coverage of corporate tax avoidance[1] and whether tax avoidance hurts firm performance given

[1]We follow Dyreng, Hanlon, and Maydew (2008) and define tax avoidance as activities that allow a company to lower its effective tax rate (ETR). It includes activities on the full tax aggressiveness continuum, from perfectly legal to gray-area or illegal tax reduction measures. Hence, avoidance is not necessarily illegal – on the contrary, modern taxation would not work as a system to encourage desired behavior and discourage undesirable behavior if companies and individuals did not seek to minimize their tax burden (e.g., Dyreng, Hanlon, and Maydew, 2008).

the media attention. On the one hand, reducing the tax burden lowers costs for the firms, which should, ceteris paribus, increase profits (Desai and Dharmapala, 2009). On the other hand, as the anecdotal evidence from above shows, consumers and the wider public seem to care about and grow increasingly critical about corporate tax avoidance. In the absence of media attention, this may be not a cause for concern for investors, but once the mass media brings this information to the public spotlight, it poses a potential threat to the brand. A key mechanism is that consumers likely prefer brands that share their norms (e.g., Kang, Germann, and Grewal, 2016), and by choosing competing products or brands, they may penalize brands that violate shared norms and community standards. Aggressive tax avoidance is likely a violation of community standards and shared norms, which implies that aggressive, publicly visible tax avoidance may hurt brand equity.

Academic research has tried to establish a link between actual tax payments and firm performance, but evidence is inconclusive. While some studies find a positive effect (e.g., Blaufus, Möhlmann, and Schwäbe, 2019), others find a negative effect (e.g., Hardeck and Hertl, 2014) or no evidence for an effect at all (e.g., Desai and Dharmapala, 2009). In addition, literature about the role of media attention is scarce and thus far limited to newspapers. Therefore, we study how media attention to corporate tax avoidance affects firm performance and follow recent calls in the literature (e.g., Chen, Schuchard, and Stomberg, 2019) and assess whether changes in the intensity and the tone of media attention to firms' tax-related activities not only in newspapers, but also in social media, affect a firm's market valuation. We base our conceptual framework on previous findings in the corporate social (ir-)responsibility literature and argue that stock prices should react negatively in response to an unanticipated increase in the volume and the negative sentiment of tax-related media coverage in newspapers and in social media. To empirically assess these conjectures, we compile a data set that comprises financial information as well as tax-related (social) media coverage for publicly listed US firms from the Fortune 500 list for a 10 year period (i.e., 2009 to 2019), which yields a data set of more than one million observations at the firm-day level. We employ a stock return response model to analyze stock market reactions to continuous unanticipated changes in the volume and valence of tax-related (social) media attention. Interestingly, the results do not provide evidence for the expected effects, and this is robust across a broad range of alternative model specifications. However, an extensive post-hoc analysis with weekly consumer-based data demonstrates that brand strength suffers from negative tax-related media coverage. This implies that consumers notice and consider the media coverage about corporate tax behavior. We further analyze the stocks' trading volumes and provide evidence that both an unanticipated increase in the volume and the negativity of (social) media attention towards corporate tax avoidance increase trading volumes. This suggests that investors actually do react to changes in the media attention variables – albeit not in a uniform pattern: some investors seem to perceive it as a negative signal and sell the respective stock, others as a positive signal that causes them to buy the stock. Hence, we conclude that the absence of evidence for a stock price effect does not mean that there is no informational value contained in media attention. Instead, the evidence suggests that the interpretation of the signal is heterogeneous across investors. Our findings add to the discussion revolving around stricter legislation in the taxation of multinational corporations. If the public and policy makers are interested in curbing corporate tax avoidance, they cannot rely solely on investors and consumers to penalize firms for their unethical tax behavior and, by this, to "educate" corporations to be more compliant with the spirit of tax laws. As far as the market valuation of affected companies is concerned, firms do not seem to be vulnerable to immediate financial damage when tax practices are critically examined by newspapers and exposed on social media.

Next, we provide an overview of relevant literature and present the theoretical framework. We then introduce the data and the modeling approach. After that, we discuss the results of the post-hoc analyses that consider brand attention, brand strength, and abnormal trading volume as dependent variables, as well as different dimensions of firm heterogeneity. We conclude with a discussion of the results and derive implications.

2.2 Literature

Prior research has tried to establish a link between tax payments and firm performance. However, empirical evidence is inconclusive as to whether and how corporate tax avoidance affects a firm's financial performance. Traditionally, corporate tax avoidance has been viewed as a transfer of value from the state to shareholders (Desai and Dharmapala, 2009), implying a positive effect of tax avoidance activities on shareholder value under the premise that tax avoidance activities are otherwise costless to firms. However, tax avoidance is likely associated with various types of (non-tax) costs, including, e.g., reputational costs, costs arising from increased scrutiny by tax authorities after a firm is first caught engaging in questionable or illegal tax avoidance, or political costs that arise from the threat of policymakers tightening the regulatory framework.

Since investors may take these potential non-tax costs into consideration, the net effect of tax avoidance is a priori unclear. While a very limited number of studies has started to study this question, the overall picture remains inconclusive. We provide an overview of all studies that we are aware of that analyze the relation between corporate tax avoidance and firm performance in Table 2.1 and highlight how our study extends this previous work.

Analyzing US firms in the 1990s, Desai and Dharmapala (2009) do not find a significant effect of tax avoidance (measured as the book-tax gap, an accounting based proxy for a firm's tax aggressiveness) on firm performance (Tobin's Q). The authors, however, do not consider the role of media attention in their study – a variable that likely plays an essential role in shaping firm performance (e.g., Stäbler and Fischer, 2020). In contrast, based on an event study, Hanlon and Slemrod (2009) find that the first press mention of its involvement in a tax shelter has a negative impact on a firm's cumulative abnormal returns in the 3-day window following the event. The authors attribute this negative stock market reaction at least partially to consumer backlash, as they find the negative effect to be more pronounced in the retail sector where firms are particularly exposed to direct customer interaction. Further, they find that the public disclosure of a firm's involvement in a tax shelter has less negative consequences if the effective tax rate (ETR) is higher. This resembles what is known as the "insurance effect" in corporate social responsibility literature (Flammer, 2013). It states that firms which engage in socially responsible actions and, hence, have a positive public image, suffer less from subsequent corporate scandals (e.g., Flammer, 2013; Godfrey, Merrill, and Hansen, 2009). Gallemore, Maydew, and Thornock (2014) replicate the findings of Hanlon and Slemrod (2009) using a larger sample of firms involved in tax shelters, but find that the negative market reaction is only short-term and is not present when the event window is extended from three to 30 days. Lab experiments conducted by Hardeck and Hertl (2014) find some evidence that consumers penalize aggressive tax-planning firms by means of a lower willingness-to-pay – a first approach to identify the underlying mechanism why abnormal returns might be negative as indicated by Hanlon and Slemrod (2009). Finally, Blaufus, Möhlmann, and Schwäbe (2019) also performed an event study using 176 tax news items regarding publicly listed German firms as events. However, contrary to Hanlon and Slemrod (2009) and Gallemore, Maydew, and Thornock (2014), the authors find no general effect for tax avoidance news. In fact, they even find a positive impact of media coverage of tax avoidance as long as the tax avoidance is described as legal (vs. illegal).

Table 2.1: Literature overview

			Dependent variable(s)		Tax avoidance variables					
Study	**Sample**	**Method**	**Investor-based metrics**	**Consumer-based metrics**	**Accounting proxy**	**Traditional media**	**Social media**	**Media negativity**	**Continuous media attention**	**Main result**
Desai and Dharmapala (2009)	862 US firms (1993–2001)	Panel data analysis	Tobin's Q	–	✓					No significant effect of tax avoidance on firm value
Hanlon and Slemrod (2009)	108 tax shelter involvements (1990–2004)	Event study	Abn. returns	–	✓	✓				Negative effect of tax shelter news on stock returns, but less severe if cash ETR is higher
Gallemore, Maydew, and Thornock (2014)	245 tax shelter involvements (1995–2005)	Event study	Abn. returns	–	✓	✓				Negative effect of tax shelter news on stock returns (short term); reverts to 0 after one month
Hardeck and Hertl (2014)	Fictitious FMCG firm	Lab experiment	–	WTP		✓				Negative effect of tax avoidance on WTP
Blaufus, Möhlmann, and Schwäbe (2019)	176 tax news items on German firms (2003–2016)	Event study	Abn. returns	–		✓				Positive effect for legal, negative for illegal tax avoidance news on stock returns
This study	462 Fortune 500 firms (2009–2019)	Stock return response model	Abn. returns Trading volume Return risk	Brand strength Brand attention	✓	✓	✓	✓	✓	No significant effect of (social) media coverage on stock returns, significant effects on consumer-based brand strength/attention and on trading volume

✓: covered in analyses · WTP: willingness-to-pay · ETR: effective tax rate

Summing it up, while Desai and Dharmapala (2009) only use regressors based on accounting data (see Column 6 of Table 2.1), Blaufus, Möhlmann, and Schwäbe (2019), Hanlon and Slemrod (2009), as well as Hardeck and Hertl (2014) operationalized tax avoidance using newspaper articles (see Column 7 of Table 2.1). While these studies have started to analyze the role of media attention in the context of corporate tax avoidance considering traditional media, the effects of tax-related media coverage with regard to firm performance seem ambiguous.

We extend these studies as follows: First, we are not aware of any research that considers *social* media attention in this context (see Column 8 of Table 2.1). Given that social media have started to dominate the public discourse in many areas it seems warranted to include these in the analyses. In addition, social media likely differ from traditional media in various ways. For example, Gorodnichenko, Pham, and Talavera (2021) note that information disseminates much faster via social media and that users express extreme views that go largely unnoticed by mainstream news outlets. Moreover, traditional news are mainly consumed passively, whereas information flow via social media also involves an active component in that users can deliberately spread information to their peers and social contacts. Second, previous research has not investigated the effect of the tonality (i.e., the sentiment) of the news articles (see Column 8 of Table 2.1). Third, unlike in an event study design, we do not conceptualize media attention as a discrete event, but rather as a continuous process (see Column 9 of Table 2.1). Hence, we do not restrict our media data to the first public mention of a firm in tax context, but investigate the volume over time (see Column 10 of Table 2.1). As our later analysis shows, media coverage of tax avoidance is not related to single events but shows continuous variation over time.

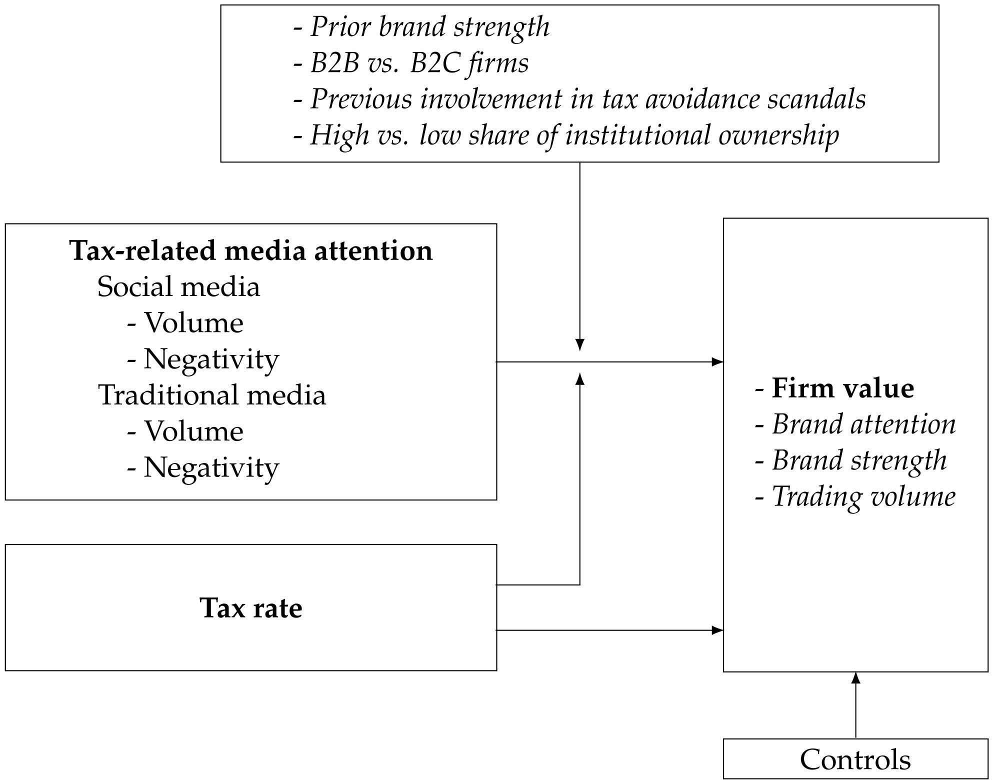
2.3 Theory and Framework

Corporate social responsibility (CSR), i.e., the contribution of business resources to the improvement of societal well-being, has been shown to be related to customers' purchase behavior (e.g., Nickerson et al., 2022) and to firm value (e.g., Kang, Germann, and Grewal, 2016). Although some studies find boundary conditions under which CSR has null or negative effects on the different metrics of firm performance, the majority of previous literature finds positive effects (Nickerson et al., 2022). Corporate social *ir*-responsibility (CSI) is the conceptual counterpart to CSR and reflects behavior that is incompatible with societal values. Empirical evidence points to asymmetric effects of CSR and CSI, such that doing bad actually harms firm performance more than doing good helps (Margolis, Elfenbein, and Walsh, 2009). CSI can be defined as corporate behavior that "negatively affects an identifiable social stakeholder's legitimate claims" (Strike, Gao, and Bansal, 2006, p. 852). If we consider the financing of the public sector expenditures as one of the main objectives of tax collection, this definition also applies to tax avoidance activities. Governments use tax money to create infrastructure, to fund education, and to provide social security and justice, among other things. This applies for taxes paid by individuals as well as for those paid by companies. In other words, the payment of taxes is a channel through which companies contribute to the common good of the economies in which they operate. To take up the definition of CSI by Strike, Gao, and Bansal (2006), this constitutes a "legitimate claim" that consumers and the society at large as "identifiable social stakeholder[s]" have on firms: If companies engage in tax avoidance and thus fail to fully meet this claim, consumers are negatively affected in that direct and indirect government benefits are potentially lower.

CSR and CSI differ in one central aspect. If a firm is involved in a CSR activity, there is an intrinsic motivation for companies to proactively report on CSR activity, whether through their own communication channels, via corporate social media accounts, or through CSR reports. If, in contrast, a company is involved in a CSI incident, there is naturally less incentive to communicate this proactively. In these cases, independent media play a crucial role in ensuring that the public becomes aware of these events (Stäbler and Fischer, 2020). Generally, it appears well established that mass media shape public knowledge and perceptions about corporate activities (e.g., Van Heerde, Gijsbrechts, and Pauwels, 2015). Bushee et al. (2010) show that the media – the business press in particular – play an important role as intermediaries in disseminating information related to earnings announcements and thus in reducing information asymmetries. In line with this notion, prior research has established that media reputation, i.e., the evaluation of a firm presented in the media, is a valuable intangible asset for firms (e.g., Pfarrer, Pollock, and Rindova, 2010). Conversely, this suggests that media coverage of large CSI events should also affect firm value (Stäbler and Fischer, 2020). Prior research, however, has been inconclusive as to whether or not media coverage of tax-related activities affects stock market valuations. Based on theoretical arguments and empirical evidence that we cite above, we conclude that the overall evidence is sufficiently strong to expect that media attention also matters in the context of corporate tax avoidance.

Figure 2.1 shows the conceptual model. We expect that a higher level of media attention to tax issues by traditional media (i.e., newspapers) will lead to a decrease in the market valuation of the respective company. Specifically, we argue that when the tone of the media attention becomes more negative and the volume increases (i.e., the interaction of volume x negativity) we expect market valuation to decline. In addition, it is likely that the extent to which consumers and the market penalize a firm for coverage about tax avoidance depends on the extent to which the firm actually engages in tax avoidance. In support of this notion, Hanlon and Slemrod (2009) document that tax payments in the past can act as an insurance against negative public scrutiny in the media. Accordingly, we expect that the negative effects of tax coverage in the media is less severe for firms that report higher actual tax payments. To test for that, we interact the media attention variables with the cash effective tax rate of a given firm. While the reasoning above is based mainly on studies focusing on traditional media formats such as newspapers, there is also a more recent stream of literature assessing the value impact of social media attention. For instance, Etter, Ravasi, and Colleoni (2019) state that, in the presence of a corporate crisis, social media contribute to forming an organizational reputation and Barkemeyer et al. (2020) find that the media landscape and particularly attention patterns changed since the rise of social media. To the best of our knowledge, social media attention to corporate tax activity has not been empirically analyzed to date, and thus we follow the call of Chen, Schuchard, and Stomberg (2019) for an expansion of research to include social media effects. We expect that social media attention has effects similar to traditional media attention and that both an increase in volume and negativity of social media attention to a firm's tax activity cause market valuation to drop.

In addition to our empirical assessment of these proposed effects, we conduct a number of post-hoc analyses to shed light on potential underlying mechanisms that give rise to the observed effects. The constructs that we consider in these post-hoc analyses are printed in italics in Figure 2.1. First, we investigate a wide range of moderators (i.e., prior brand strengths, B2B vs. B2C firms, previous involvement in tax avoidance scandals, high vs. low share of institutional ownership). We explain the operationalization of these moderators in Appendix A.1. Furthermore, we investigate additional dependent variables such as consumer-based brand strength and brand attention, as well as trading volume to provide further insights into the underlying mechanism why and under which conditions firm value may change as a result of tax-related media coverage.



Note: All constructs that we analyze in our post-hoc analyses are printed in italics.

Figure 2.1: Conceptual framework and expected effects

2.4 Data

We estimate our model based on a data set comprising the publicly listed firms that were part of the 2018 Fortune 500 list of the largest US-based companies by revenue. We collect stock market and firm financial data from *Thomson Reuters Datastream* and access *Twitter* and *LexisNexis* to obtain (social) media attention data. The observation period is between January 2009 and April 2019. We provide an overview of the variables in Table 2.2.

2.4.1 Firm financial data

We use daily firm level stock market data and consolidated quarterly accounting data for the observation period from Thomson Reuters Datastream for 462 publicly traded firms that appeared on the 2018 Fortune 500 list of the largest US-based firms by revenue.[2] We directly obtain the market capitalization per firm and trading day. The market capitalization is the product of the stock price and the number of shares outstanding, and it reflects the market valuation of a firm. We compute the (realized) stock returns $R_{i,t}$ for firm i as the growth rate of the market capitalization between two subsequent trading days t (e.g., Mizik and Jacobson, 2008). Around stock splits, share consolidations, or similar events, the market capitalization data is less reliable, leading to unreasonably high or low return rates (e.g., the number of shares outstanding is updated only with a few days of delay after a stock split, which temporarily causes the market valuation to artificially drop). We exclude those 0.01 percent of our observations for which the calculated $R_{i,t}$ is farther than two standard deviations away from the sample average. This leaves us with 1,009,816 firm-trading day observations, for which all daily variables are available. We present descriptive statistics for the financial data in Table 2.3. We also report the definitions and descriptive statistics for the variables that we consider in our post-hoc analyses (Section 2.7) in Tables 2.2 and 2.3. In addition to the daily stock market data, we also retrieve financial information published in the firms' quarterly and annual reports. These include sales as well as return on assets (ROA), which is the net income divided by total assets times 100. A crucial variable in this research is the cash effective tax rate (cash ETR), which is a measure that is frequently used in literature to assess a firm's (inverse) tax aggressiveness (e.g., Hanlon and Slemrod, 2009). It is the ratio of cash taxes paid (as reported in a firm's cash-flow statement)

[2] The remaining 38 firms are non-publicly traded companies such as privately owned mutual insurance companies, or we have to drop them due to ambiguities in the firm names (see Section 2.4.2).

Table 2.2: Measures and descriptions

Variable	Notation	Description	Data source
Firm financial variables			
Market capitalization	$MktCap_{i,t}$	Market capitalization ($stock\ price * no.\ of\ outstanding\ shares$) of firm i on trading day t	Thomson Reuters Datastream
Stock returns	$R_{i,t}$	Stock returns $((MktCap_{i,t} - MktCap_{i,t-1})/MktCap_{i,t-1})$ of firm i on trading day t (vs. $t-1$)	Own computations
Net income	$NetInc_{i,q}$	Net income of firm i in quarter q	Thomson Reuters Datastream
Total assets	$Assets_{i,q}$	Total assets of firm i in quarter q	Thomson Reuters Datastream
Sales	$Sales_{i,q}$	Sales of firm i in quarter q	Thomson Reuters Datastream
Return on assets	$ROA_{i,q}$	Return on assets $((NetInc_{i,q}/Assets_{i,q}) * 100)$ of firm i in quarter q	Own computations
Cash effective tax rate	$CashETR_{i,y}$	Cash effective tax rate $(CashTaxesPaid_{i,y}/(PretaxIncome_{i,y} - ExtraordinaryItems_{i,y}))$ of firm i in fiscal year y	Own computations
Media attention variables			
Article volume	$ArticleVol_{i,t}$	Number of news articles mentioning firm i in tax-related context on trading day t	LexisNexis
Article negativity	$ArticleNeg_{i,t}$	Average negativity of all news articles mentioning firm i in tax-related context on trading day t	Own computations
Tweet volume	$TweetVol_{i,t}$	Number of tweets mentioning firm i in tax-related context on trading day t	Twitter API
Tweet negativity	$TweetNeg_{i,t}$	Average negativity of all tweets mentioning firm i in tax-related context on trading day t	Own computations
Dependent variables for post-hoc analyses			
Brand strength	$BrandStr_{i,w}$	Index that indicates how strong a brand is in the minds and hearts of consumers in week w. It is a measure aggregated across six brand perception dimensions such as quality, value, satisfaction, recommendation, identification, and overall impression (for details see Appendix A.2).	YouGov
Brand attention	$BrandAtt_{i,w}$	Index that indicates whether respondents have heard anything positive or negative about the brand in week w (for details see Appendix A.2).	YouGov
Trading volume	$TradVol_{i,t}$	Trading volume (i.e., the aggregated volume of all trades in USD) of firm i on trading day t	Thomson Reuters Datastream

Table 2.3: Descriptive statistics

	N	Min.	$Q_{0.25}$	Median	Mean	$Q_{0.75}$	Max.	SD
Firm financial variables								
$MktCap_{i,t}$ [a]	1,009,816	10.2	5,130.1	12,314.1	31,913.9	30,956.8	1,120,880	61,158.6
$R_{i,t}$	1,009,816	-0.102	-0.008	0.001	0.001	0.009	0.103	0.019
$Sales_{i,q}$ [a]	16,366	1.2	1,642.7	2,670.2	6,103.8	5,485.1	138,793	10,697.5
$ROA_{i,q}$	16,366	-31.347	0.577	1.267	1.468	2.241	94.504	2.127
$CashETR_{i,y}$	4,348	0	0.126	0.227	0.228	0.324	0.500	0.136
Media attention variables								
$ArticleVol_{i,t}$	1,009,816	0	0	0	0.068	0	32.000	0.415
$ArticleNeg_{i,t}$	1,009,816	0	0	0	0.001	0	0.116	0.005
$TweetVol_{i,t}$	1,009,816	0	0	0	8.308	0	64,988.000	189.876
$TweetNeg_{i,t}$	1,009,816	0	0	0	0.019	0	0.744	0.060
Dependent variables for post-hoc analyses								
$BrandStr_{i,w}$	52,202	-0.783	0.159	0.328	0.393	0.599	1.706	0.325
$BrandAtt_{i,w}$	52,202	-6.508	-2.406	-1.704	-1.764	-1.061	1.098	0.982
$TradVol_{i,t}$	1,000,414	0	948,702.8	2,144,744.5	5,427,629.5	4,828,666.5	1,880,988,680	22,805,300.7

[a] Values presented in million USD.

to the pre-tax income less extraordinary items in the same period (see Table 2.2). Data on the taxes paid is available on an annual level. Following Hanlon and Slemrod (2009), we winsorize cash ETRs at 0 and 50 percent to avoid extreme outliers. ETRs are unavailable for 14 percent of all firm-years due to incomplete coverage in the $CashTaxesPaid$ variable. We therefore impute the firm-specific mean cash ETRs for the missing values to not lose valuable information from these observations (note that otherwise a single missing value in the annual cash ETR would imply losing all daily observations of an entire firm-year). We show in one of the robustness checks (Appendix A.3, Table A.3) that this decision is not consequential for our focal results. Finally, we observe 16,366 firm-quarter and 4,348 firm-fiscal year combinations.

2.4.2 Media attention data

We consider media attention data of two distinct types: traditional media attention derived from newspaper articles and social media attention from Twitter. For both types of media attention, we create a volume measure that captures the number of articles/tweets in which a firm was mentioned in a tax-specific context as well as a valence measure to measure how negatively the firm has been portrayed. Our extensive data collection yields about 35,000 relevant news articles and 9 million tweets that meet our search criteria. We present the data collection process and the measurement below.

Traditional media attention

We access the news database LexisNexis to collect all news articles that were published between January 2009 and April 2019 in *The New York Times*, *The New York Post*, *The Washington Post*, and *Investor's Business Daily*, and that mentioned a firm name from our sample in conjunction with the term "tax". The selected newspapers are at different positions in the political spectrum, include broadsheet, specialist business, and tabloid news, and we assume that the topics covered and the overall sentiment are reflective of what other outlets report as well (Van Heerde, Gijsbrechts, and Pauwels, 2015).

Different variants and alternatives of firm names pose an obstacle to reliably identifying *all* firm mentions no matter the name that is used to refer to the company. In a first step, we therefore compile a list of alternative references to a firm, including abbreviations (e.g., *GM* for *General Motors*), different spellings (e.g., *Walmart* and *Wal-Mart*), different names for parent and subsidiary company (e.g., *Alphabet* and *Google*), as well as commonly used "nicknames" (e.g., *Fannie Mae* for the *Federal National Mortgage Association FNMA*). We develop this list in multiple steps: First, we collect a set of over 10,000 firm-unspecific business news articles. On this corpus of news articles, we run a named-entity recognition (NER) algorithm which is used to automatically detect entities in unstructured text and to classify them into predefined categories, such as organizations or firms (Thomas and Sangeetha, 2019). We semi-automatically match the NER-based list of recognized firm mentions with our Fortune 500 company name list. Specifically, we calculate a matrix of string distances that allows us to identify the most similar strings for each Fortune 500 firm name. This step is helpful to identify different spellings of the same firm name, however it does not help in finding abbreviations or entirely different names for the same company as long as they are not orthographically similar. For this reason, we perform a manual web search in a second step, where we systematically scan the introductions of the Wikipedia articles of each firm for alternative names. In a typical Wikipedia article, the first sentence contains references to potential alternative company names.[3] With this list of alternative firm names, we move on to actually access the news articles of interest by performing a keyword search in the

[3]For instance, the introductory sentence in the Wikipedia article about the computer firm Hewlett-Packard reads as follows: "*The original incarnation of the Hewlett-Packard Company, commonly shortened to Hewlett-Packard [...] or HP, was an American multinational information technology company headquartered in Palo Alto, California [...]*"; from: https://en.wikipedia.org/wiki/Hewlett-Packard (last access: April 11, 2023)

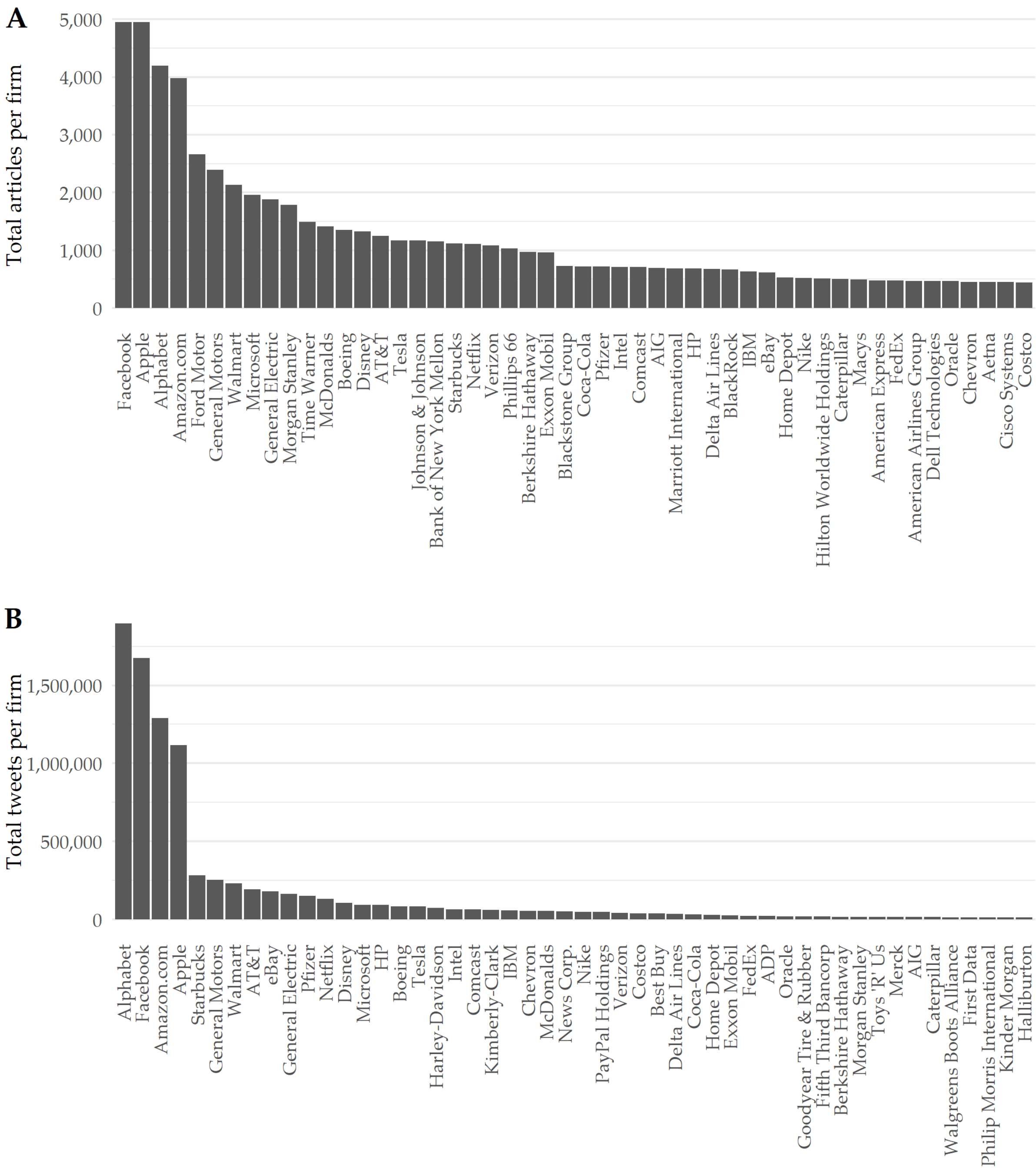
LexisNexis news archive. We require that the articles for our sample contain the word "tax" and at least one reference to at least one firm from our firm universe.

We define a set of rules to ignore firm references which likely have nothing to do with the article content. For instance, we disregard references to Facebook and Twitter if they appear in close proximity to the phrases "join" or "follow", as these are likely calls to interact with a social media page rather than comments on the corporate tax behavior of Facebook or Twitter.[4] Further, we drop firms for which we cannot reliably distinguish between meaningful and irrelevant references (e.g., the financial services company *S&P Global* is often mentioned in the context of homonym stock indeces, such as the *S&P 500* or the *S&P Dow Jones* index, where the reference is not reflecting media attention towards the firm) or where the firm name per se is ambiguous and is likely to appear in the tax context with a different meaning (e.g., *Progressive* or *Target*). This procedure leaves us with a total of 34,645 relevant news articles that mention at least one firm from our sample. We define a reference to a firm within an article as *firm mention*. Firm mentions are binary and measured on an article-firm level. Hence, an article can contain multiple firm mentions for different firms. In the 34,645 articles, we identified 82,959 firm mentions, i.e., on average, an article contains references to 2.4 different firms. We find firm mentions to be very unevenly distributed across firms, as can be seen in Panel A of Figure 2.2. Few firms receive a lot of attention in the newspapers, whereas many firms are mentioned only very rarely.

Article volume. We aggregate the firm mentions to the firm-trading day level and define article volume $ArticleVol_{i,t}$ as the absolute number of articles across all news outlets that mention firm i on trading day t in conjunction with the term "tax". News articles published on a weekend or a trading holiday are attributed to the next trading day because this is the next chance for an investor to incorporate the new information into her investment decisions. We present descriptive statistics for the media attention variables in Table 2.3.

Article negativity. To compute a measure of article negativity, we rely on a dictionary-based approach suggested by Chen, Schuchard, and Stomberg (2019). Generic sentiment dictionaries are not well suited to assess the negativity in this context due to the very specific vocabulary that is used to describe tax activities. The words "shift", "deal", or "shelter", for example, may have a neutral or even positive connotation in most contexts, whereas they hint at inappropri-

[4]A considerable number of articles published in *The New York Times* end with the clause "*Follow The New York Times Opinion section on Facebook, Twitter (@NYTopinion) and Instagram, and sign up for the Opinion Today newsletter.*"



Distributions of articles (Panel A) and tweets (Panel B) across firms (showing top 50 firms ranked by number of firm mentions)

Figure 2.2: Distribution of media attention across firms

ate behavior or have a negative connotation in the specific context of corporate taxes. For this reason, Chen, Schuchard, and Stomberg (2019) compiled a custom dictionary of words that allows researchers to measure the degree of negative tone in media tax coverage. We slightly adapt the original dictionary provided by Chen, Schuchard, and Stomberg (2019) to also detect lexical variations of the words contained (for the full dictionary see Appendix A.5). To assess negativity, we follow the approach by Chen, Schuchard, and Stomberg (2019) and determine the percentage of negative words in every individual article using the dictionary. Finally, we take the average negativity of all articles mentioning firm i on day t and define this value as $ArticleNeg_{i,t}$. For firm-trading day combinations for which we observe no article, we impute a negativity of zero. The logic is that we consider the absence of articles as a meaningful signal that there is nothing negative for the media to report. With regard to our focal results, this decision has no consequences compared to imputing the firm-level average negativity (see Appendix A.3, Table A.4). Note that the large proportion of zeros in the negativity variable as shown in Table 2.3 is due to the sparsity in the article volume, i.e., many firms have few or no article mentions.

Social media attention

To measure social media attention to corporate tax behavior, we collect data from Twitter. Twitter has not only grown to be an increasingly relevant news provider (Barkemeyer et al., 2020), but communication on Twitter is public (unlike, e.g., Facebook where many posts are private), and it operates an application programming interface (API) that allows for full archive search of all public tweets (Rust et al., 2021). We search the Twitter history for tweets mentioning a firm from our list of (alternative) Fortune 500 firm names in conjunction with the term "tax". We omit the same firms from the social media data that we dropped in the cleaning process of the traditional news article data. Among them are also companies that contain ambiguities that are specific to social media language (e.g., the *PPL Corporation* had to be omitted since "ppl" is also a common acronym for "people" in social media). This yields a total of 9,057,587 tweets in the observation period between January 2009 and April 2019. As in the case of newspaper articles, firm mentions are very unevenly distributed in tweets with some firms being mentioned very often and many that receive comparably little attention (Panel B in Figure 2.2).

Tweet volume. In line with our approach for traditional media, we measure $TweetVol_{i,t}$ as the total number of tweets that mention firm i on a given trading day t. Again, we attribute social media attention that takes place on weekends and trading holidays to the subsequent trading day. We report summary statistics for the tweet volume variable in Table 2.3. While the majority of observations sees no tax-related tweets, the maximum number of tweets for a firm-trading day combination is 64,988.[5]

Tweet negativity. A tweet is a short message of at most 280 characters (until 2017 the maximum was only 140 characters) that users of the platform Twitter post publicly. Tweets are much shorter than newspaper articles and the style of the language used on Twitter often differs substantially from that in newspapers. The sentiment dictionary established by Chen, Schuchard, and Stomberg (2019) was originally compiled for assessing the tone of newspaper articles and it turns out to be inadequate to also reliably measure the negativity in tweets. We therefore employ a deep learning approach using a deep neural network (DNN) to obtain negativity values for every tweet. To this end, we let two independent judges who are not authors of this paper manually label a random sample of 2,000 tweets. The question that we ask the judges to address is: *"On a scale from 0 (not negative at all) to 4 (extremely negative), how negatively do you perceive this tweet regarding the tax morale of the mentioned company?"*. By explicitly directing our question towards the tax morale of the focal firm, we make sure that not the general tone of the tweet is rated but the specific tone directed to the company's tax activity. This implies that a tweet that has an extremely negative tonality, but is not actually related to a firm's tax behavior, should be rated with a negativity of zero. By cross-checking a sample of labels assigned by the judges, we ensure that judges have implemented the instructions as we intended. We take the average ratings of the two judges and rescale values to the [0,1] space. We design a DNN with a sigmoid activation function which is capable of performing regression tasks and generating continuous negativity predictions between 0 and 1 (Chollet and Allaire, 2018). We use 1,600 of the previously labeled tweets to train and validate the DNN (the validation set comprises 20 percent of the 1,600 training examples). The remaining tweets are held back to test the model on unseen data. Among a range of different tested model architectures, we find a specification with two hidden layers (an embedding layer and a dense layer) and a dense output layer to yield the lowest mean absolute error (MAE) in the validation data. We train the selected DNN for 16 epochs, using the "rmsprop" optimizer. To avoid that our DNN learns from firm names

[5]This observation belongs to Apple on August 30, 2016. On this day, the EU Commission sentenced Apple to pay 13 billion euros in back taxes that had previously been evaded with the "Double Irish" agreement (European Commission, 2016).

instead of the substantive content of the tweets, we remove all firm names from the data prior to the training. By this, we want to make sure that firm names per se do not make a tweet more or less negative, but that two tweets are evaluated the same if the firm name is the only thing that changes. Even after removing the firm names, the network shows a good performance in predicting the negativity in our test sample with an out-of-sample MAE of 0.196 *without* versus 0.167 *with* firm names. Transformed back to the [0,4] scale in which the tweets have been labeled, this indicates an average deviation of less than 1 negativity point from the raters' judgements. We use the DNN to predict the negativity for each tweet from the entire tweet data. The distribution of negativity values in the unlabelled tweets is very similar compared to that of the hand-labelled training data. Reading through a number of randomly selected tweets and checking the corresponding negativity predictions also had a reasonable face validity (see Appendix A.4 for examples of tweets and their respective negativity scores). We show summary statistics for the tweet negativity variable in Table 2.3.

2.4.3 Fama-French-Carhart factors

In our analyses we decompose observed stock returns into expected and abnormal returns. A common way in the literature to explain stock returns is the Fama-French-Carhart four-factor model (Carhart, 1997; Fama and French, 1993). We obtain trading day-level time series for the market risk premium $Rm_t - Rf_t$ and the outperformance factors SMB_t, HML_t, and WML_t (see Appendix A.6 for variable descriptions and summary statistics). $Rm_t - Rf_t$ is the overall market risk premium, or the excess return on the market. It is defined as the overall market returns compared to a risk-free alternative, i.e., the return rate of a one-month Treasury bill (Fama and French, 1993). SMB_t, HML_t, and WML_t, respectively, represent the excess returns on trading day t of small versus big firms, high versus low book-to-market firms, and previous period winning versus losing stocks.[6]

[6]For details see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios.html and http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html (last access: April 11, 2023)

2.5 Model

We employ a stock return response model as proposed by Mizik and Jacobson (2004). Stock return response models are frequently used in the marketing literature to assess the value relevance of (marketing) measures above and beyond contemporaneous accounting information (e.g., Mizik and Jacobson, 2008; Nam and Kannan, 2014; Srinivasan et al., 2009). In regressing abnormal (i.e., unexpected) returns on a metric of interest, stock return response models provide insights into the question of whether this metric contains incremental information for investors over accounting information in explaining stock returns (Mizik and Jacobson, 2004). By relying on the efficient market hypothesis (Fama, 1970; Srinivasan and Hanssens, 2009), stock return response models are theoretically similar to event studies with the main difference that stock return response models estimate the market reaction to a dynamic and non-discrete process that happens over a longer time span instead of a discrete event (Mizik and Jacobson, 2008). Given that (social) media attention to tax behavior has a continuous character as per our descriptive statistics (e.g., after a tax avoidance incident, media attention may increase, then, after a while, it eventually drops and perhaps picks up momentum again once new information becomes public), we consider a stock return response model very well suited for our data. In robustness checks, we also employ an event study, which does not alter our main results.

2.5.1 Estimates of unanticipated components

We construct measures for the unanticipated deviations from expected levels of our variables. First, we transform our focal dependent variables $R_{i,t}$ to obtain "abnormal" stock returns by relying on the Fama-French-Carhart four-factor model (Carhart, 1997; Fama and French, 1993) which is a well-established procedure (Srinivasan and Hanssens, 2009). For every firm i, we estimate a regression model of the following form:

$$R_{i,t} - Rf_t = \alpha_i + \beta_i * (Rm_t - Rf_t) + s_i * SMB_t + h_i * HML_t + w_i * WML_t + \varepsilon_{i,t} \tag{2.1}$$

with R_i, $Rm_t - Rf_t$, SMB_t, HML_t, and WML_t as defined in Appendix A.6 (Table A.10), α_i, β_i, s_i, h_i, and w_i being the regression coefficients, and the idiosyncratic error $\varepsilon_{i,t}$. We define the residuals $\hat{\varepsilon}_{i,t}$ from these firm-level regressions as our measure for abnormal returns $AbnRet_{i,t}$, which is the dependent variable in the stock return response model.

In line with Mizik and Jacobson (2008), we define sales growth over two subsequent quarters $U\Delta SalesGrowth_{i,q} = log(Sales_{i,q}) - log(Sales_{i,q-1})$ as our unanticipated sales measure. For the unanticipated component of the ROA, we estimate a fourth-order autoregressive process (AR(4)) with firm fixed effects using the time-demeaned (lagged) ROA values as predictors for the current-period ROA. We define the residuals of this regression as our unanticipated ROA measures $U\Delta ROA_{i,q}$. The AR(4) process has the following form:

$$\begin{aligned}(ROA_{i,q} - \overline{ROA_q}) = \alpha_i &+ \phi_1 * (ROA_{i,q-1} - \overline{ROA_{q-1}}) \\ &+ \phi_2 * (ROA_{i,q-2} - \overline{ROA_{q-2}}) \\ &+ \phi_3 * (ROA_{i,q-3} - \overline{ROA_{q-3}}) \\ &+ \phi_4 * (ROA_{i,q-4} - \overline{ROA_{q-4}}) + \varepsilon_{i,q}\end{aligned} \tag{2.2}$$

Next, we focus on the media attention variables. Here, we assume *all* tax-related media attention to be unanticipated. This follows the reasoning that, if a firm does nothing to be reported about or commented on (which should be the default), media volume and negativity are equal to zero. All deviations from zero can therefore be perceived as unexpected or unanticipated. If there should nonetheless be a baseline tax media attention for certain firms that is different from zero, then this is still adjusted for by our inclusion of firm fixed effects. We compute the cash ETR, a commonly used measure of (inverse) tax aggressiveness (e.g., Hanlon and Slemrod, 2009), on an annual basis as described in Section 2.4. We define the first differences of the cash ETR as our measure of unanticipated tax aggressiveness $U\Delta CashETR_{i,y}$.

2.5.2 Stock return response model

In our stock return response model specification, we use the unanticipated measures for both our dependent and the independent variables that we derived above. To align the quarterly and annual accounting data with the daily stock market data, we use for every day the last data point in the accounting data that has been made available to investors and the wider public in a quarterly/annual report. If, for example, firm i published their sales to be \$100 million in their quarterly report on June 30, then we use this value (or the unanticipated component of it) for all days in the subsequent quarter until a new value is made public in the next quarterly report on September 30. We introduce our proposed model specification in Equation 2.3.

$$
\begin{aligned}
AbnRet_{i,t} = &\sum_{m=1}^{2} \beta_m * log(volume+1)_{m,i,t} + \sum_{m=1}^{2} \gamma_m * negativity_{m,i,t} \\
&+ \phi * U\Delta CashETR_{i,t} \\
&+ \sum_{m=1}^{2} [\zeta_m * log(volume+1)_{m,i,t} * negativity_{m,i,t}] \\
&+ \sum_{m=1}^{2} [\rho_m * log(volume+1)_{m,i,t} * U\Delta CashETR_{i,t}] \\
&+ \sum_{m=1}^{2} [\theta_m * negativity_{m,i,t} * U\Delta CashETR_{i,t}] \\
&+ \sum_{j=1}^{3} \delta_j * controls_{j,i,t} + \eta_i + \eta_{weekday} + \eta_{year} + \varepsilon_{i,t}
\end{aligned}
\tag{2.3}
$$

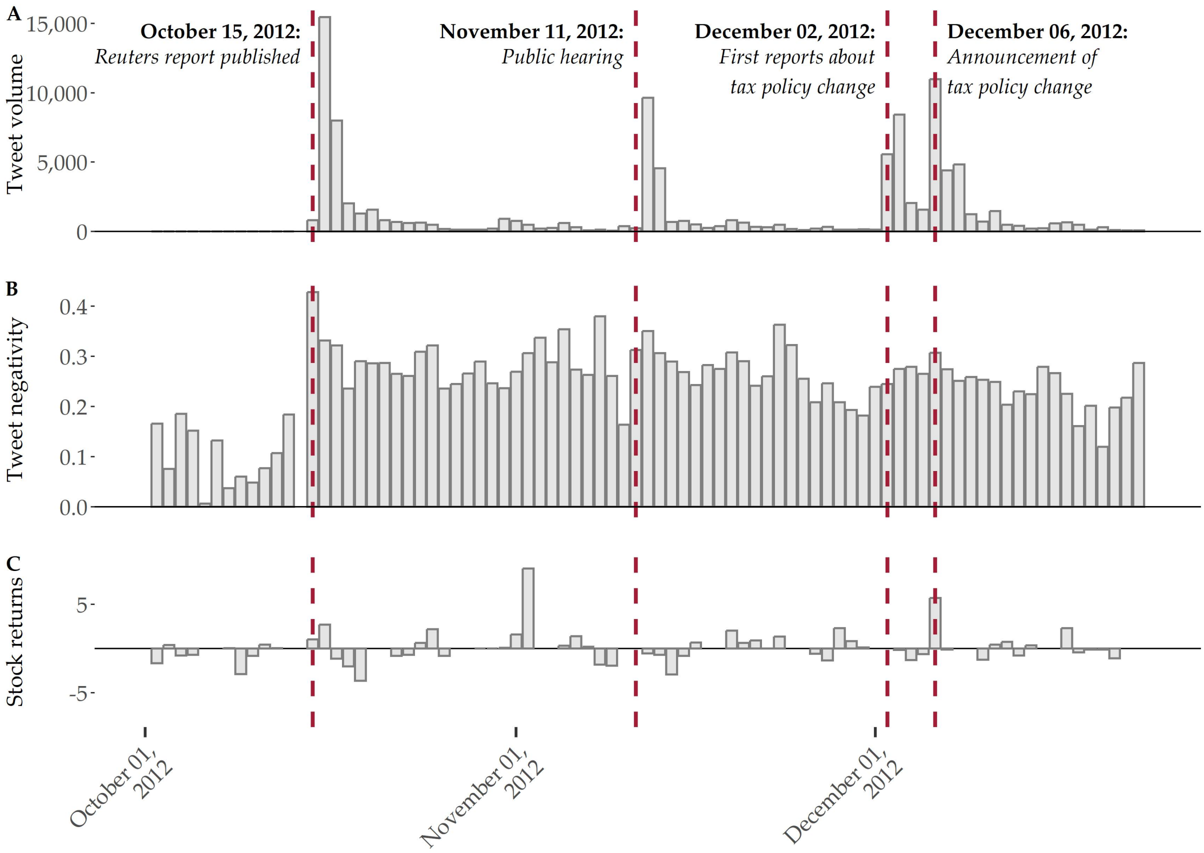
In the full model, we regress the abnormal returns on the log of both types of media volume m (i.e., on article volume and tweet volume), on the media attention negativities, on their interactions, on the unanticipated changes in the cash effective tax rates $U\Delta CashETR$, as well as on the interactions between the media attention variables and the cash ETRs. We add one to the media attention volumes so that the logarithm is defined for all observations. On top of that, we also include control variables j (i.e., $U\Delta ROA$, $U\Delta Sales$, and a dummy variable $afterHoliday$, which is equal to 1 if the respective trading day follows a holiday and 0 otherwise). Finally, we include firm, weekday, and year fixed effects to adjust for unobserved heterogeneity across these dimensions. We mean-center all numeric variables before computing the interactions. We estimate models that separately either consider traditional media or social media alongside the focal model specification that contains both. In the remainder of this article, we refer to the model specification from Equation 2.3 as "full model". We refer to the model that only uses traditional media (social media) as "articles model" ("tweets model").

2.6 Results

We start by revisiting model-free results for the case of Starbucks UK in 2012. We then show the regression results of our focal analysis before we discuss our robustness checks.

2.6.1 Model-free evidence – the case of Starbucks UK

To support the validity of the media attention measures that we propose, we take a closer look at the example of Starbucks. The Seattle-based coffeehouse chain, as described in the introduction, was subject to substantial public scrutiny after the news agency *Reuters* revealed Starbucks UK's aggressive tax avoidance practices in October 2012. Figure 2.3 shows the development of tweet volume (Panel A) and negativity (Panel B), as well as the stock returns (Panel C) during this period, and we highlight the key events of this development, as described in the introduction, with red dashed lines. Prior to the first report of the tax avoidance practices, the volume



Note: The tweet volume in early October prior to the publishing of the Reuters report (Panel A) is just above zero and therefore indistinguishable from the horizontal axis.

Figure 2.3: Stock returns and social media during Starbucks UK tax avoidance crisis

of tweets mentioning "Starbucks" in conjunction with "tax" is close to zero and negativity is on a fairly low level. Then, on October 15, the number of tweets rises sharply and negativity peaks. As information around the Reuters special report spreads, the number of tweets hits its peak the day after the publication of the report and quickly returns to a moderate level over the next few days. Relative to the overall (i.e., non-tax-specific) tweet volume for Starbucks, this corresponds to an increase from 0.0001 percent in the two weeks prior to the first event to about 7 percent tax-related tweets in the two weeks thereafter. The negativity of the tweets, in turn, seems to be affected more persistently and remains at a level higher than the initial level for a much longer time. This pattern repeats itself for the tweet volume after the subsequent events on November 11, December 2 and 6. The increases in the tweet negativity of subsequent events is less pronounced, as negativity is already on a relatively high level before these events. As for stock market movements in the observed time window, it is more difficult to identify a consistent pattern. For the events on October 15, November 11, and December 2, there seems to be a slightly delayed negative reaction. The announcement of the additional tax payments on December 6 – although related Twitter comments were generally negative – seems to coincide with positive returns in the stock market. Overall, based on the visual inspection, we conclude that the measures of social media attention that we propose contain meaningful variation in response to changes in what is known about a firm's tax conduct.

2.6.2 Stock return response model

We present the results of our stock return response model for all three specifications introduced above in Table 2.4. Interestingly, and in contrast to our expectations, we do not find evidence that media attention to corporate tax avoidance matters for investors to the extent that firm value changes. While the interaction of article volume and article negativity is negative, it is not significant. In fact, none of the coefficients among the media attention variables are significant. The control variables generally show face-valid results. Unanticipated increases in ROA lead to higher abnormal returns. $U\Delta CashETR$, the unexpected change in the cash effective tax rate has a negative coefficient, suggesting investors negatively value an increase in the tax payments. We do not find evidence that sales growth affects abnormal returns, i.e., the coefficient is insignificant. In the following, we present a battery of robustness checks and discuss potential explanations that may lead to these results.

Table 2.4: Stock return response model (focal model specifications)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	0.0003 (0.0002)	0.0003 (0.0002)	
$ArticleNeg$	γ_1	0.0037 (0.0073)	0.0033 (0.0073)	
$log(TweetVol + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg$	γ_2	0.0002 (0.0004)		0.0002 (0.0004)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.0209 (0.0134)	-0.0203 (0.0133)	
$log(TweetVol + 1) * TweetNeg$	ζ_2	0.0000 (0.0002)		-0.0000 (0.0002)
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)**	-0.0003 (0.0002)**	-0.0003 (0.0002)**
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	-0.0013 (0.0013)	-0.0010 (0.0012)	
$ArticleNeg * U\Delta CashETR$	θ_1	0.0284 (0.0473)	0.0278 (0.0469)	
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.0003 (0.0002)		0.0002 (0.0002)
$TweetNeg * U\Delta CashETR$	θ_2	0.0001 (0.0022)		0.0002 (0.0022)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0001 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0001)*	-0.0001 (0.0001)*	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0003 (0.0002)	0.0003 (0.0002)	0.0003 (0.0002)
N		1,009,816	1,009,816	1,009,816
Adj. R^2		0.033	0.033	0.033
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

2.6.3 Robustness checks

To assess the robustness of our results to various modeling choices, we run a battery of robustness checks. As a first robustness check, we omit all interactions from the models and regress abnormal returns on the main effects only (Appendix A.3, Table A.5). We then run models that allow for delayed investor responses in that we define the media volume variables as the sum of the volumes over the past three trading days (days t, $t-1$, and $t-2$) and negativities as the rolling averages of the negativities of the past three trading days (Appendix A.3, Table A.6). Next, we use the focal model, but use the untransformed realized returns of the period instead of the abnormal returns that we had estimated with the Fama-French-Carhart model (Appendix A.3, Table A.7). In a further robustness check (Appendix A.3, Table A.9), we interact our focal variables with the year variable to test for a potential time trend in the effects of media attention. Again, we do not find substantially different results from those of our focal model specification.

Finally, while media coverage of tax avoidance shows continuous variation over time, abnormal returns might only vary as a response to the *first* press mention of its involvement in tax shelters. As a result, investigating tax-related media coverage over time may potentially bury the "new" information with regard to the tax avoidance under too much noise (i.e., large variation in the dependent and independent variables over time). This may (potentially) be the cause of the non-significant results. To identify whether this is true, we investigate the impact of these tax-related events independent from the variation over time and follow the principal idea of an event study (e.g., Hanlon and Slemrod, 2009). We use peaks of the continuous media coverage variables to identify single tax avoidance-related events (for details on how we identify the events, see footnotes of Table 2.5). We use a wide range of common event windows to identify the immediate effect of tax avoidance-related events on cumulative abnormal returns (CAR) (e.g., Stäbler and Fischer, 2020). The results of Table 2.5 demonstrate that the CARs associated with individual tax avoidance events are all insignificant. We take this robustness across different model specifications as evidence that the unexpected findings are not due to specific modeling choices.

Table 2.5: Event study results

	Variant 1[a]		**Variant 2[b]**		**Variant 3[c]**		**Variant 4[d]**	
Number of events	1,263		522		4,555		124	
Number of firms	163		95		210		52	
Event windows	**Mean**	**p-value**	**Mean**	**p-value**	**Mean**	**p-value**	**Mean**	**p-value**
AR [0]	0.06%	0.15	0.03%	0.62	0.01%	0.79	0.03%	0.74
CAR [-1,0]	0.03%	0.64	0.13%	0.15	-0.01%	0.75	0.12%	0.39
CAR [-1,1]	0.09%	0.30	0.09%	0.41	0.01%	0.69	0.16%	0.39
CAR [-1,2]	0.15%	0.09	0.11%	0.37	0.01%	0.73	0.15%	0.54
CAR [-1,3]	0.13%	0.20	0.08%	0.57	0.03%	0.52	0.10%	0.73

[a] We identify events based on the interaction effect of media volume and negativity. Whenever the interaction effect exceeds a threshold (i.e., a value larger than 10 times the S.D. + mean), we identify the peak of the interaction as an event. In this setting, we consider preceding events only after a minimum of 14 days. Note, that we also test alternative selection rules and come to the same conclusions.
[b] We identify events based on articles that are exclusively tax avoidance specific. Specifically, we used the following search terms to identify these articles: "tax (haven | avoidance | shelter | advantage)". We identify an event as an event if at least 2 articles have appeared within the first 7 days after the initial article. Again, in this setting, we consider preceding events only after a minimum of 14 days.
[c] We follow the approach of variant 2 and identify articles through selective search terms. However, we do not apply any additional selection rules. We still come to same conclusions.
[d] We follow the approach of variant 2 and identify articles through selective search terms. However, we identify an event as an event if at least 4 articles have appeared within the first 7 days after the initial article. In addition, we consider preceding events only after a minimum of 30 days.

2.7 Post-Hoc Analyses

The results presented in Section 2.6 are at odds with our a priori expectations. In particular, we expected that increased negative media attention to a firm's tax avoidance would reduce firm value, but the estimation results do not support these expectations. In the following, we identify possible explanations for the non-significant effects of media attention on abnormal stock returns and try to empirically evaluate these explanations. In Table 2.6, we present an overview of all supplementary analyses, including the robustness checks from Section 2.6.3, analyses exploring potential heterogeneity in the effect across firms (see Section 2.7.1), as well as further post-hoc analyses where we study effects on alternative dependent variables (see Sections 2.7.2, 2.7.3, and 2.7.4). With this abundance of additional analyses, we aim to better understand our null results from Section 2.6, and to narrow down the set of possible explanations.

2.7.1 Firm heterogeneity

First of all, it is possible that our null findings are caused by firm heterogeneity that we may not have accounted for. Potentially, the magnitude and perhaps even the direction of the effect of unexpected changes in media attention on abnormal returns may be heterogeneous across firms. Not accounting for this may lead to the situation that positive and negative effects offset each other, and potential effects may disappear in aggregate analyses. To assess the plausibility of this alternative explanation, we perform a battery of additional analyses using different sub-samples of the data. To this end, we split our sample across several dimensions: we distinguish between B2C versus B2B-focused firms, between firms with a high and a low share of institutional (as opposed to individual) investors, and we analyze subsets of firms that are publicly known to have been involved in major tax avoidance issues. Across all different subsets, the results are quite consistent with the focal estimates that we presented above. Even when additionally restricting the sample in terms of time (e.g., around the publication of the *LuxLeaks* or *ParadisePapers*), the substantive results of the analyses remain virtually unchanged (see Appendix A.1 for details on the sample splits).

Table 2.6: Overview of robustness checks and post-hoc analyses

	Robustness checks					
	(1)	(2)	(3)	(4)	(5)	
Specification	Main effects only	Delayed investor responses	Untransformed realized returns as DV	Interaction with time trend	Event studies	
Main conclusions	Unchanged	Unchanged	Unchanged	Unchanged	Unchanged	
Detailed results	Appendix A.3: Table A.5	Appendix A.3: Table A.6	Appendix A.3: Table A.7	Appendix A.3: Table A.9	Table 2.5	
	Firm heterogeneity					
	(6)	(7)	(8)	(9)	(10)	(11)
Specification	B2C vs. B2B firms	High vs. low share of institutional investors	Known involvement in aggressive tax avoidance	Starbucks only	Unpooled firm-specific analysis	Moderation with prior brand strength
Main conclusions	Unchanged	Unchanged	Unchanged	Unchanged	Unchanged	Unchanged
Detailed results	Appendix A.1: Table A.1	Appendix A.1: Table A.1	Appendix A.1: Table A.1	Appendix A.1: Table A.1	Appendix A.7: Figures A.1–A.4	Appendix A.8: Table A.16
	Post-hoc analyses					
	(12)	(13)	(14)	(15)		
Specification	Consumer brand attention as DV	Brand strength as DV	Trading volume as DV	Idiosyncratic risk as DV		
Main conclusions	Significantly affected by media attention	Significantly affected by media attention	Significantly affected by media attention	Significantly affected by media attention		
Detailed results	Table 2.7	Table 2.7	Table 2.8	Table 2.9		

As model-free evidence, we had introduced the case of Starbucks UK to illustrate the public's reaction to corporate tax avoidance. To give further credence to our findings, we re-run the model for the single firm Starbucks in the late year of 2012. Even for this very selective subsample, for which we know that substantial variation in volume and negativity of media attention occurred, the focal coefficients remain insignificant. As an additional measure to identify potential systematic firm heterogeneity in the effect sizes, we repeat our analyses in an unpooled setting at the firm level, i.e., we estimate one regression per firm. We report the estimated firm-specific coefficients graphically and list the firms with the highest and lowest estimates for each focal regressor in Appendix A.7. Again, the overwhelming majority of firm-specific estimates is insignificant, and we cannot discern a pattern that would suggest the omission of other important moderator variables.

Finally, we tested the potential moderating role of prior firm brand strength. While some research shows that brand equity insures a firm from the adverse effects of crisis events (Ahluwalia, Burnkrant, and Unnava, 2000; Eilert et al., 2017; Hsu and Lawrence, 2016), others have documented that brand equity can have a boomerang effect during such crises (Mafael, Raithel, and Hock, 2022) or social irresponsibility events, in general (Stäbler and Fischer, 2020). We obtain consumer based brand strength measurements from *YouGov*, a global market research company, for all 146 firms from our sample for which YouGov collects this measure. Brand strength is a combined measure of six dimensions, i.e., brand value, brand quality, brand satisfaction, brand recommendation, brand identification, and brand overall impression (for details, see next section and Appendix A.8). In line with prior literature (Stäbler and Fischer, 2020), we measure prior brand strength as the four-week rolling average, lagged by one week. We re-estimate Equation 2.3, and consider both the main effect and the interactions of prior brand strength with tax-related media attention. We find no evidence that prior brand strengths moderates the relationship between tax-related media coverage and abnormal returns (see Appendix A.8 for details). In light of these findings across these different analyses, we cautiously conclude that firm heterogeneity is not a likely explanation for the null findings that we presented above. We now discuss potential alternative explanations.

2.7.2 Impact on consumer-based firm metrics

In this section, we discuss possible mechanism leading to the insignificant effects of negative tax-related media coverage on firm value, by looking at consumer-based firm metrics. A first potential explanation for the null findings could be that investors are torn between the potential benefits and downsides of corporate tax avoidance. On the one hand, consumers and the society are increasingly critical about corporate tax avoidance. A key mechanism is that consumers likely prefer to purchase products from brands that share societal norms and that care about the society they operate in (e.g., Kang, Germann, and Grewal, 2016). As a result, consumers may penalize brands that avoid taxes as it is a violation of community standards and shared norms, leading to lower sales and profits. On the other hand, extensive tax reductions lower costs for the firms, which should increase profits. As a result, investors may conclude that positive and negative value implications cancel each other out. If the data are consistent with this explanation, we should observe that consumers become aware of the increased media coverage, and that they view affected brands more negatively. We therefore use weekly consumer evaluation data from the market research company *YouGov*, covering close to 10 years (May 2009 to April 2019). YouGov is a global market research company specializing in online panels that monitor the largest firms in the US across all relevant consumer sectors. This enables us to investigate the impact of tax-related media coverage for all 146 B2C-firms (all firms from our sample of 462 firms that are covered by YouGov). This yields 52,218 firm-week observations. The weekly firm ratings, aggregated across trading days, are based on responses of a large sample of at least 300 randomly drawn consumers (e.g., Hewett et al., 2016).

Specifically, YouGov provided us with the aggregate measures of brand attention and brand strength, which are widely used in marketing research (e.g., Colicev et al., 2018; Hewett et al., 2016; Luo, Raithel, and Wiles, 2013; Stäbler and Fischer, 2020). Conceptually, both consumer-based firm performance dimensions relate to the consumer-based brand equity model (Keller, 1993) which consists of brand awareness and brand image. This enables us to investigate whether consumers become aware of the news of corporate tax avoidance and whether this influences their perceptions about the firm.

Brand attention represents the number of respondents who are aware of either negative or positive news about a brand. It is a relative measure that runs from 0 to 100 (percent). *Brand strength* is a multidimensional index that runs from -100 to $+100$. It represents how strong a brand is in the minds and hearts of consumers (Luo, Raithel, and Wiles, 2013; Stäbler and Fischer, 2020). Appendix A.2 provides the exact wording used in the YouGov surveys and more details on the YouGov measurements. Recall that the measurements of brand attention and strength are restricted to an upper and lower limit (e.g., 0 and 100). Consequently, we apply a logit transformation to the measurements of brand attention and brand strength to enable a linear estimation that satisfies the range restrictions and the assumption of a normally distributed error (see Appendix A.2 for details). Several marketing studies have used this transformation, including studies on brand crises (e.g., Cleeren, van Heerde, and Dekimpe, 2013). Our results, however, arise independent of whether or not we apply the transformation.

We consider all tax-related media attention variables (e.g., volume, negativity, and its interaction) and firm financial variables (e.g., cash effective tax rate) as used in the stock return response model as regressors (see Equation 2.3). To be aligned with the weekly periodicity, however, we consider the total volume and the average negativity of all news (or Twitter) articles in the calendar week and include firm, calendar week, and year fixed effects. Again, we mean-center all numeric variables. We then re-estimate Equation 2.3 with brand attention and brand strength as dependent variables.

Table 2.7 shows the results both for brand attention and brand strength. We consider two alternative specifications for each metric. First, we consider the (logit) transformed absolute values of brand attention and strength. Second, in line with prior research (Hansen, Kupfer, and Hennig-Thurau, 2018), we consider the *changes* of brand attention and strength by subtracting from the transformed value of the focal week the mean of the transformed values of the four prior weeks (i.e., ΔBrandAttention and ΔBrandStrength).

We find a robust effect across all estimated models showing that an increase in the number of negative tax-related news articles increases consumer attention and reduces brand strength values, however, only if the news articles are negative. The interaction term of article volume and article negativity is significantly positive for attention both in the equation with brand attention measured in levels ($\zeta_1^{BrandAttention} = 1.629$, $p < .10$), as well as in the specification with the dependent variable in differences ($\zeta_1^{\Delta BrandAttention} = 1.036$, $p < .01$). Likewise, the interaction is significantly negative for brand strength in both specifications ($\zeta_1^{BrandStrength} = -0.897$, $p < .05$ and $\zeta_1^{\Delta BrandStrength} = -0.179$, $p < .01$). Thus, negative news coverage of tax avoidance does hurt firms with regard to consumer evaluations. Interestingly, we only find the effects for negative newspaper coverage and not for negative tweets. Possibly, consumers perceive information communicated through traditional news media as more trustworthy and credible than news communicated on social media platforms (e.g., Karlsen and Aalberg, 2021). We also measured variations of the models (e.g., only including articles or tweets) and come to the same conclusions.

Table 2.7: Consumer-based firm metric models

		Dependent Variable: Consumer-based firm metrics			
		BrandAttention	ΔBrandAttention	BrandStrength	ΔBrandStrength
$log(ArticleVol+1)$	β_1	0.025 (0.013)*	-0.001 (0.004)	0.005 (0.008)	0.002 (0.001)
$ArticleNeg$	γ_1	-0.067 (0.607)	-0.105 (0.207)	0.089 (0.264)	-0.029 (0.041)
$log(TweetVol+1)$	β_2	0.017 (0.007)**	0.005 (0.002)***	0.005 (0.003)	-0.000 (0.000)
$TweetNeg$	γ_2	-0.015 (0.031)	-0.045 (0.016)***	-0.020 (0.018)	-0.003 (0.004)
$log(ArticleVol+1)*ArticleNeg$	ζ_1	1.629 (0.961)*	1.036 (0.271)***	-0.897 (0.439)**	-0.179 (0.066)***
$log(TweetVol+1)*TweetNeg$	ζ_2	0.025 (0.021)	-0.002 (0.006)	-0.008 (0.010)	0.000 (0.002)
$U\Delta CashETR$	ϕ	0.135 (0.079)*	0.006 (0.006)	-0.017 (0.036)	-0.003 (0.001)**
$log(ArticleVol+1)*U\Delta CashETR$	ρ_1	0.131 (0.101)	0.066 (0.033)**	-0.014 (0.044)	0.001 (0.006)
$ArticleNeg*U\Delta CashETR$	θ_1	-4.015 (3.398)	-3.229 (1.428)**	-0.522 (1.594)	0.038 (0.263)
$log(TweetVol+1)*U\Delta CashETR$	ρ_2	0.005 (0.036)	-0.000 (0.007)	0.001 (0.016)	0.000 (0.001)
$TweetNeg*U\Delta CashETR$	θ_2	0.158 (0.295)	0.114 (0.094)	0.024 (0.132)	-0.012 (0.025)
$U\Delta ROA$	δ_1	0.000 (0.003)	-0.000 (0.001)	0.000 (0.002)	-0.000 (0.000)
$SalesGrowth$	δ_2	0.051 (0.021)**	0.014 (0.005)***	0.005 (0.005)	0.001 (0.001)
N		52,202	52,202	52,202	52,202
Adj. R^2		0.906	0.005	0.922	0.000
Firm, weekday, and year FEs		yes	yes	yes	yes

* p < .1, ** p < .05, *** p < .01

2.7.3 Impact on trading volume

Past research has shown that not only stock prices but also trading activity (i.e., trading volume) may react to new information in the market (Kim and Verrecchia, 1991) and that information dissemination can affect trading activity through two channels. One channel pertains to changes in how informed investors are. A second channel goes via the the consensus, i.e., the extent of agreement among investors (Holthausen and Verrecchia, 1990; Rees and Twedt, 2022). The level of trading activity of a certain asset is captured by its trading volume. The trading volume (introduced in Section 2.4 as $TradVol_{i,t}$) denotes the absolute volume (in USD) of trades on a given day, i.e., it reflects the sum of the absolute value of all transactions (purchases and sales) of a stock. We argue that by assessing whether or not trading volume increases after changes in tax media coverage may help us in narrowing down the set of potential explanations for our null findings in the stock return response model. *First*, it is possible that investors do not perceive the variation in media attention as news and that the information that the media reports is already known to them from sources that we do not observe in our model. This would imply that the information is already accounted for by investors and factored into stock prices before it is then captured in our media attention variables. The consequence would be insignificant effects of media attention on abnormal stock returns. *Second*, if investors perceive the variation in the media attention as news, but they conclude that positive and negative value implications cancel each other out, we would again observe the null effects that we find in our analysis. *Third*, investors may simply view media attention on tax avoidance as irrelevant for future expected cash flows. Importantly, if one of these three potential explanations would hold true, the *trading volume* would not be affected by unanticipated changes in the media attention variables. *Fourth*, investors may actually perceive changes in the media attention to tax-related activities as news and adapt their trading behavior in response. However, it is possible that the assessment of whether this is beneficial for future cash flows or not *differs across investors*. If this explanation was true, the effect of media attention on stock returns may be insignificant, while we would observe an increase in trading volume in this situation (Holthausen and Verrecchia, 1990). To gauge which of these potential explanations is the most plausible, we repeat the analyses with abnormal trading volume as the dependent variable. We present the results in Table 2.8.

In the model specification $TradVol\ 1$ in Column 1, we define abnormal trading volume as a stock's daily trading volume divided by the average trading volume of this stock over the prior month (i.e., 20 trading days) to capture deviations from the average trading volume of this stock. We regress the log of this ratio on all independent variables and interactions from the stock return response model and, following Rees and Twedt (2022), and on the aggregated abnormal returns over the past week (5 trading days), $PriorAbnRet(Week)$, and month (20 trading days), $PriorAbnRet(Month)$ as additional control variables. We provide alternative specifications of the trading volume model with models $TradVol\ 2$ and $TradVol\ 3$. $TradVol\ 2$ is based on the approach of Rees and Twedt (2022) and does not use firm fixed effects. Instead, the difference between daily trading volume and prior month average trading volume is scaled by the number of shares outstanding. Finally, model $TradVol\ 3$ takes the log of the absolute daily trading volume without isolating an abnormal component (for an overview of all model equations, see Appendix A.9). All specifications yield qualitatively similar results with respect to our parameter estimates of interest.[7] The parameter estimates of the direct effects of media attention on trading volume are consistently positive and significant throughout all specifications. As with

[7]Table 2.8 shows a slight reduction in the sample sizes as compared to the stock return response model. This is caused by missing values in the trading volume variable. We have no reason to suspect that values are missing systematically, and a re-estimating the stock return response model with the reduced sample from the trading volume model confirms this (see Appendix A.3, Table A.8).

Table 2.8: Trading volume models

		DV: Alternative operationalizations of trading volume		
		$TradVol$ 1	$TradVol$ 2	$TradVol$ 3
$log(ArticleVol + 1)$	β_1	0.06 (0.01)***	263.18 (202.40)	0.06 (0.02)***
$ArticleNeg$	γ_1	0.65 (0.32)**	15,583.68 (6230.04)**	2.28 (1.17)*
$log(TweetVol + 1)$	β_2	0.01 (0.00)***	47.23 (37.31)	0.00 (0.01)
$TweetNeg$	γ_2	0.03 (0.01)**	810.29 (229.55)***	0.12 (0.05)***
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.65 (0.53)	1,924.13 (10043.77)	-2.08 (1.48)
$log(TweetVol + 1) * TweetNeg$	ζ_2	-0.03 (0.01)***	-441.95 (232.07)*	-0.09 (0.03)***
$U\Delta CashETR$	ϕ	-0.00 (0.00)	17.51 (65.25)	0.07 (0.05)
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	-0.02 (0.03)	-1,153.49 (788.56)	0.01 (0.11)
$ArticleNeg * U\Delta CashETR$	θ_1	2.60 (1.33)*	68,309.70 (26897.18)**	2.93 (2.89)
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.00 (0.01)	-15.57 (178.70)	-0.05 (0.04)
$TweetNeg * U\Delta CashETR$	θ_2	-0.08 (0.09)	-1,239.28 (1415.70)	0.07 (0.21)
$U\Delta ROA$	δ_1	0.00 (0.00)	-12.88 (7.08)*	-0.02 (0.00)***
$SalesGrowth$	δ_2	-0.00 (0.00)	18.60 (27.48)	-0.01 (0.01)
$afterHoliday = True$	δ_3	-0.16 (0.01)***	-1,141.84 (187.61)***	-0.16 (0.01)***
$PriorAbnRet(Week)$	δ_4	0.06 (0.04)	-389.82 (2420.66)	0.19 (0.03)***
$PriorAbnRet(Month)$	δ_5	-0.15 (0.02)***	-2,030.07 (338.50)***	-0.21 (0.04)***
N		992,214	992,196	993,766
Adj. R^2		0.010	0.003	0.880
Weekday, and year FEs		yes	yes	yes
Firm FEs		yes	no	yes

* p < .1, ** p < .05, *** p < .01

DV TradVol 1: $log(TradVol/PriorAvgTradVol(Month))$

DV TradVol 2: $(TradVol - PriorAvgTradVol(Month))/SharesOutstanding$

DV TradVol 3: $log(TradVol + 1)$

the stock return response model from our main analysis, we again provide an alternative model specification where we allow for delayed investor responses (see Appendix A.10, Table A.17). Again, the results are qualitatively similar.

The fact that the effects of the regressors that capture media attention negativity are also positive and significant indicates that the trading activity increases if tax-related news reporting and/or social media conversations become more negative, ceteris paribus. The negative interaction effects between tweet volume and negativity suggests that the incremental positive effects of an additional tweet (i.e., an increase in media volume) becomes less strong if media reporting is more negative on average. This may arise due to a dilution effect: a few very negative tweets are more influential and stand out stronger and thus have a larger effect on trading volume compared to a situation where the same negativity is present across a large number of tweets. The results indicate that investors *do* perceive and decode changes in the media attention to tax-related activities. However, this effect seems to be heterogeneous across investors. While some perceive the same piece of information as a signal to buy a stock, others value the information negatively and sell the stock. In consequence, the trading volume increases. This interpretation of our results is in line with arguments made for example by Holthausen and Verrecchia (1990), Bamber, Barron, and Stober (1999) or Rees and Twedt (2022), who refer to this heterogeneity in investors' interpretations as (lack of) *"consensus"*, as *"differential interpretations"*, or as (lack of) *"precision of the signal"*, respectively.

2.7.4 Impact on idiosyncratic risk

Research at the marketing-finance interface has not only considered the effect of marketing strategies on stock returns, but also on stock returns *risk* (e.g., McAlister, Srinivasan, and Kim, 2007; Tuli and Bharadwaj, 2009). Seminal work by Markowitz (1952) and Sharpe (1964) has broken down the risk of an asset into systematic risk (i.e., market-related risk; the beta estimates in the regressions from Equation 2.1) and unsystematic, or idiosyncratic, risk. Systematic risk, is an inherently long-term construct that tends to change only little over time (McAlister, Srinivasan, and Kim, 2007), which is why we only estimate one time-constant beta coefficient for every firm in our observation period. Idiosyncratic risk, on the other hand, is the amount of risk that is left once all systematic risk is accounted for. Hence, it reflects volatility in returns that is mainly caused by a firm's actions (Sorescu and Spanjol, 2008; Tuli and Bharadwaj, 2009) and therefore shorter-term fluctuations are possible. Besides mere returns, risk is another metric relevant to the market that analysts use to judge the performance of a stock (Tuli and Bharadwaj, 2009). Consistent with this theoretical consideration, and to test whether returns risk might help explaining the increase in abnormal trading volumes, we investigate in the following whether a firm's idiosyncratic risk is adversely affected by changes in media attention variables. Following Tuli and Bharadwaj (2009), we measure idiosyncratic risk using the standard deviations in a firm's abnormal returns for every fiscal year. We aggregate our media attention variables to the same annual level by taking the sum of volumes and the average of the daily negativities over a fiscal year and we regress idiosyncratic risk on the resulting annual media attention variables, the cash ETR reported in the respective fiscal year, on interaction terms as introduced in previous models, and on a set of control variables. We report the results of the analyses in Table 2.9.

While most coefficients are insignificant, we find some evidence that the average article negativity positively affects idiosyncratic returns risk. Hence, signals in the market regarding more negative tax-related media reporting about a firm seem to go hand in hand with an increase in

Table 2.9: Idiosyncratic risk models

		DV: Idiosyncratic risk		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	-0.0001 (0.0002)	-0.0001 (0.0001)	
$ArticleNeg$	γ_1	0.6212 (0.2353)***	0.5658 (0.2311)**	
$log(TweetVol + 1)$	β_2	-0.0000 (0.0001)		0.0000 (0.0001)
$TweetNeg$	γ_2	-0.0077 (0.0079)		-0.0057 (0.0078)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.1105 (0.0329)***	-0.1003 (0.0345)***	
$log(TweetVol + 1) * TweetNeg$	ζ_2	0.0006 (0.0011)		0.0007 (0.0010)
$U\Delta CashETR$	ϕ	0.0002 (0.0005)	0.0002 (0.0005)	0.0002 (0.0005)
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	0.0003 (0.0005)	0.0005 (0.0005)	
$ArticleNeg * U\Delta CashETR$	θ_1	-0.2582 (0.3874)	-0.1311 (0.3369)	
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.0003 (0.0003)		0.0003 (0.0003)
$TweetNeg * U\Delta CashETR$	θ_2	0.0036 (0.0197)		-0.0052 (0.0175)
ROA	δ_1	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
$log(Sales + 1)$	δ_2	-0.0016 (0.0003)***	-0.0016 (0.0003)***	-0.0016 (0.0003)***
N		4,348	4,348	4,348
Adj. R^2		0.718	0.718	0.717
Firm and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

the volatility of returns (i.e., an increase in both upward and downward returns risk). The consequence may be that the lack of precision in the signal makes it harder for investors to formulate clear expectations about expected returns of a stock, which may result in the increase in trading volumes that we find.

2.8 Conclusion

In this research, we analyze the question of whether media attention to corporate tax avoidance is harmful for firm value. Previous research in marketing has not considered the potential brand damage that may arise from this financially consequential strategic decision of the firm. Theoretical considerations suggest that consumers care about a brand's corporate behavior, and that consumers may penalize brands that violate a society's norms by engaging in corporate tax avoidance. In that case, rational investors would incorporate this into their investment behavior, which in turn would imply that stock returns for a given firm would be lower if corporate tax avoidance becomes public and the reputational damage is expected to be larger than the cost savings. To assess these theoretical expectations, we collected data on media coverage (approx. 35,000 news articles and approx. 9 million tweets) of the tax conduct of close to 500 of the largest US firms across 10 years, information on the firms' tax payments, as well as a set of accounting-based covariates. Using a stock return response model, we analyze whether media attention to corporate tax avoidance is associated with changes in abnormal stock returns. In contrast to our expectations, we do not find evidence that media attention to corporate tax avoidance harms firm value, i.e., across a wide range of specifications, we do not find evidence that either the volume or the valence of the coverage of tax-related articles and tweets, or their interactions, matters for firm value.

There is a number of potential explanations for these null findings. First, it is possible that consumers do not notice corporate tax avoidance and the associated media attention, and that they do not perceive it as relevant for their decision making. The findings from our post-hoc analyses, however, suggest that this is not a likely explanation because we find that brand attention increases and brand strength decreases in response to changes in media attention to corporate tax avoidance. A second potential explanation is that investors do not perceive the variation in media attention as news and that the information that the media reports is already known to them from sources that we do not observe in our model. This would imply that the information is already accounted for by investors and factored into stock prices before it is then captured in our media attention variables. While the insignificant effects of media attention on abnormal returns are consistent with this explanation, the significant effects on trading volume are not. Based on these findings we conclude that investors respond to unexpected changes in the media attention, but not in a uniform or homogeneous way (Bamber, Barron, and Stober, 1999). Some investors interpret the signal as positive, likely under the assumption that a potential consumer backlash will not be substantial, and the financial benefit of paying less in taxes may outweigh potential consumer backlash. Other investors likely come to a different conclusion and are more pessimistic about potential consumer backlash, and these investors will sell the respective stocks.

We view this ambiguous response by investors as evidence for a weak imprecise signal from the media regarding the underlying consumer behavior that we described above, leading to a lack of consensus on how to interpret this signal. This also implies that the majority of investors does not view media attention to tax avoidance as sufficiently relevant and the majority does not believe that it affects consumer behavior and associated future expected cash flows. Through these analyses and findings, we provide a number of insights that are new to the literature, and we thus make a valuable contribution to extant research that allows us to better understand the potential reputational damage of seemingly unrelated firm decisions that marketing has not paid attention to in the past. We now discuss the key findings in detail and derive implications for the society, policy makers, and firms.

2.8.1 Discussion of the findings

Consumers notice media attention to a firm's tax avoidance. The results that we provide above suggest that media attention to tax avoidance does not go unnoticed. Consumer attention to tax-avoiding brands increases, whereas the brand strength perceptions decrease. This is evidence that concerns about reputational costs of tax avoidance are in principal warranted because consumers care about the firms' conduct, even in a seemingly remote area like corporate taxes. This finding is important because it sheds light on potential consumer backlash as the underlying mechanism that may be of concern to investors if it is of substantial magnitude. To put the estimated effects into perspective, we compute effect sizes (based on the results in Table 2.7, Column 3). Following prior literature on CSI (e.g., Stäbler and Fischer, 2020), we increase the focal regressors (article volume and article negativity) each by two standard deviations and investigate how brand strength values change when all variables are set to their sample average. We find a reduction in brand strength of 3.8 percent due to this change in negative tax related media coverage. According to *Interbrand*'s "Best Global Brands" ranking (Interbrand, 2022), the average monetary value of the 100 most valuable brands is $30.889 billion (per brand). Hence, a two standard deviation increase in media coverage about tax avoidance (both in terms of volume and valence) translates to an average reduction in monetary brand value of $1.173 billion.

Media attention to a firm's tax avoidance does not appear to reduce firm value. Our analyses do not provide evidence that news about tax avoidance activities is harmful for firm value and that companies need to fear direct negative impacts from media attention to tax avoidance in terms of decreased stock returns. The results that we discussed above suggest that there are indeed investors who penalize news about corporate tax avoidance and factor it negatively into their respective valuation of the company, but there are apparently just as many who take it as a positive signal. We conclude that investors consider but differ in their assessment of the signal from media attention to corporate tax avoidance and the consumers' reaction. The effects on consumer brand metrics and the stocks' trading volume provide the empirical basis for this conclusion.

Corporate tax avoidance appears to differ from corporate social irresponsibility (CSI). Previous research has established that consumers care about corporate social irresponsibility (CSI) and that, accordingly, CSI negatively affects firm value (e.g., Kang, Germann, and Grewal, 2016). In contrast, responsible behavior (CSR) has been shown to be positively associated with firm value. Usually, previous research has viewed tax avoidance strategies as one facet of CSI, and paying a fair share of taxes as a facet of CSR (e.g., Avi-Yonah, 2014; Hoi, Wu, and Zhang, 2013). The findings that we presented above suggest that the relation between corporate tax avoidance and firm value differs compared to how CSI is related to firm value because – despite the substantial magnitude of taxes that are avoided by firms – consumers do not react sufficiently negative to evoke negative investor reactions. This implies that corporate tax avoidance does not appear to be just another facet of CSI to which consumers and investors react in the same way they react to other instances of CSI. It rather suggests that corporate tax avoidance is a distinct construct that should be considered separately from CSR and CSI.

2.8.2 Implications for the society, public policy makers, and firms

Market mechanisms do not prevent corporate tax avoidance. In principal, consumers are in the position to penalize firms that engage in aggressive tax avoidance (e.g., Kang, Germann, and Grewal, 2016). Suppose a consumer is in the market for a pair of sneakers and she has the choice between two pairs of shoes she likes that are produced by two competing brands, one of which is known for aggressive tax avoidance. She can now choose to purchase the brand that does not engage in tax avoidance. If a sufficiently large number of consumers behaved in this way, sales would decline when a firm's tax avoiding behavior is publicized, and firm value would decline. Although we see that consumer brand valuation is negatively affected, apparently, not enough consumers behave in this way, and hence, firms are not forced by consumers to discard their tax avoidance strategies, i.e., consumers do not penalize tax avoiding firms to an extent that a majority of shareholders would see this as a sufficiently strong and precise signal about an imminent threat to future cash flows of the firm. In other words, we can conclude that market mechanisms do not prevent corporate tax avoidance.

If current market mechanisms are not effective in preventing corporate tax avoidance, what can policymakers do to reduce the extent of unwanted tax avoidance? This question is relevant because policymakers apparently care about the topic of corporate tax avoidance. In the European Union, for instance, policymakers recently adopted legislation that requires EU-wide country-by-country reporting of tax payments.[8] In light of our findings, however, we do not have reasons to expect that this rule will have substantial impact. The reason is that it relies solely on the principle of *public knowledge* about corporate tax avoidance. Our results, however, suggest that knowledge is not what is lacking. The firms that we cover and their tax avoiding behavior is covered in hundreds or thousands of news articles and dozens of thousands of tweets, i.e., the media create transparency regarding the tax avoidance behavior, but the consumer reaction is not strong enough to induce a capital market reaction.

At the same time, other research has documented that firms care about reputational damage in the context of tax payments. One example is Dwenger and Treber (2022) who find that the announcement of a naming-and-shaming policy in Slovenia for tax debt enforcement reduced

[8]The public country-by-country-reporting is an EU directive that requires multinational companies to, among other things, break down tax payments by all countries in which the company operates, including low-tax countries. It is supposed to increase tax transparency and has been approved in June 2021. For details, see here: https://ec.europa.eu/info/business-economy-euro/company-reporting-and-auditing/company-reporting/public-country-country-reporting_en (last access: April 11, 2023)

the tax debts of firms. This setting differs from what we study because Dwenger and Treber (2022) consider whether tax *debts* are paid, whereas we study the extent to which firms owe taxes, and not paying taxes that a firm owes may be more harmful for a firm's reputation compared a priori minimizing how much you owe. In addition, the Slovenian example included a normative component that clearly categorizes the outstanding payments as socially unacceptable. It is possible that measures like the global minimum tax[9], as adopted by 130 countries around the world in July 2021, may be a sharper blade to curb tax avoidance because it may allow for a more normative assessments of firms' tax avoiding behavior, e.g., in cases in which a firm pays less than the minimum rate. In sum, we conclude that policymakers cannot rely on transparency and the market alone if they seek to curb corporate tax avoidance, but rather that policy measures are required instead.

Managerial implications. Prior research has concluded that investments in non-tax CSR seem to pay off in terms of firm value (Kang, Germann, and Grewal, 2016). In contrast, this research suggests that investments in tax-related CSR (i.e., not engaging in tax avoidance) do not pay off. Hence, the findings suggest that it is advisable for firms to avoid tax payments within applicable legal boundaries and rather invest in other, visible CSR activities. It is clear, and we would like to emphasize this, that such a solution is unlikely to be optimal for the society as a whole, but this would be the firm value maximizing strategy given our results. Instead of interpreting this as a "carte blanche" for companies to minimize tax payments by all means, we believe that these findings hold important implications for policy makers that we discussed above. At the same time, it is advisable that managers track and observe the (social) media coverage of corporate tax avoidance as it exerts some influence on both consumers and investors. For example, our results help management quantify and potentially forecast damage to brand strength.

While the brand damage that we identify in our data is not directly associated with lower average stock returns, the effect is still of economic significance. As our simulation analysis demonstrates, brand managers face a loss in brand value of hundreds of millions of dollars in a single week of negative tax-related news. To what degree this brand damage effect may translate in a negative stock market effect in the long-run is unclear as of now, and it is not guaranteed that this relationship will remain insignificant. It is possible that, should customer

[9]Under the leadership of the OECD, 130 nations agreed on a minimum corporate tax rate of 15 percent in early July 2021. For details, see here: https://www.oecd.org/newsroom/130-countries-and-jurisdictions-join-bold-new-framework-for-international-tax-reform.htm (last access: April 11, 2023)

attention and the decrease in brand strength reach a tipping point, that investors start reacting negatively. A wide range of academic papers (e.g., Johansson, Dimofte, and Mazvancheryl, 2012; Mizik and Jacobson, 2008) already indicate that consumer-related metrics correlate with stock returns, which underlines the relevance for managers to collect, track, and process such consumer-based data frequently. At the same time, prior research has also demonstrated that investor perceptions might deviate from the perceptions of consumers. For example, some research studies on CSI (Groening and Kanuri, 2013; Stäbler and Fischer, 2020) find no evidence that the stock market generally punishes firms, even though consumers respond in a negative way (Ahluwalia, Burnkrant, and Unnava, 2000; Dutta and Pullig, 2011). It is a topic for future research to identify potential tipping points when initial consumer reactions translate into stock market changes.

Furthermore, while firms heavily invest into social media, they should not underestimate the power of traditional news media. Surprisingly, this study finds that consumers seem to primarily care about traditional newspaper coverage, potentially because it is considered as more trustworthy than social media (e.g., Karlsen and Aalberg, 2021) or because the interactions on Twitter are not representative of average consumers' evaluations. Thus, firms should also continue to nurture their relations to traditional media and closely monitor the volume and sentiment of the coverage there, as it continues to set the tone of the public discourse.

2.8.3 Limitations

We acknowledge that our research is subject to limitations, which may stimulate future research. First, our media attention volumes are collected with a keyword search filtering for documents that contain the term "tax" jointly with a firm name. This yields documents that are tax specific and not tax avoidance specific. The reason for this procedure is that especially on Twitter users talk about tax avoidance in very diverse ways and thus the search term "tax" is the only one that ensures that all tweets dealing with tax avoidance are included in the data. We mitigate this limitation by constructing our negativity variables to explicitly target tax *avoidance*.

Second, in an ideal world, we would not only have access to stock market data, but also to consumer demand data (e.g., sales) at a comparable level of aggregation. However, this information would only be available for a much smaller set of firms, which would severely limit the cross-sectional dimension in our data.

Finally, our research cannot provide answers to the question of where exactly the heterogeneity between investors lies when it comes to evaluating changes in media attention to tax behavior. We do find that there is heterogeneity, but do not have investor-level data available that would allow deeper analyses and hence leave this to future research. Despite these limitations, we believe that the findings from this study help better understanding the value implications of engaging in tax avoidance as well as the role of (social) media attention. We hope that our findings can help inform policymakers on implementing the right measures to effectively counter tax avoidance.

3

Paying Taxes to Calm Tempers?
The Moderating Role of Effective Tax Rates on Value Implications of Corporate Misdeeds

David Gremminger

Statement of contribution

This chapter constitutes a slightly modified version of the working paper "Paying Taxes to Calm Tempers? The Moderating Role of Effective Tax Rates on Value Implications of Corporate Misdeeds". I, David Gremminger, am the sole author of this chapter. I confirm sole responsibility for the design of the study, for data preparation, for the analysis and interpretation of the results, as well as for manuscript preparation.

Acknowledgements: The author gratefully acknowledges Daniela Mast for her excellent feedback on an earlier version of the manuscript. Further, the author acknowledges support by the state of Baden-Württemberg through bwHPC.

Abstract

Consumers are growing more and more concerned with how companies contribute to society and what sociopolitical positions they embrace. Companies have meanwhile acknowledged this development and are increasingly highlighting their investments in socially responsible initiatives. Academic research has established that, generally, socially responsible activities tend to be beneficial and socially irresponsible activities harmful for firm financial performance. However, it is unclear how the payment of taxes, i.e., the transfer of corporate resources to the state and thus indirectly to society as a whole, affects the relations between corporate social performance (CSP) and firm financial performance. Theory suggests that, by paying a higher tax rate (i.e., by refraining from aggressive tax planning), firms might be able to dampen negative effects of other types of socially irresponsible behavior. To test this, I study the firm performance implications of involvements in corporate social responsibility (CSR), corporate social irresponsibility (CSI), as well as the moderating effect of tax payments. In my sample of almost 400 of the largest US firms across 10 years, as hypothesized, I find that CSI negatively affects firm performance, as measured by Tobin's Q. In addition, I find evidence for this negative effect being positively moderated by the effective tax rate, suggesting that firms indeed seem to be able to mitigate the consequences of corporate misdeeds by paying more in taxes. For CSR, on the other hand, I do not find the expected positive effect. Post-hoc analyses hint to the notion that this is driven by the large share of short-term oriented institutional investors in my sample of large-cap firms.

3.1 Introduction

In a world where information about a company's activities is increasingly accessible to the public, consumers are growing more concerned with how companies contribute to societies in which they operate and what stance managers take on sociopolitical questions (Bénabou and Tirole, 2010; Bhagwat et al., 2020; Hambrick and Wowak, 2021; Nickerson et al., 2022). Meanwhile, this development has also been acknowledged by influential representatives from the business community. In 2019, the *Business Roundtable*, a lobbyist alliance of influential CEOs from major US corporations, released a statement that redefined their understanding of the purpose of a corporation (Business Roundtable, 2019). This statement received a great deal of attention, as it revokes the decades-old dictum of only maximizing shareholder value (aka *shareholder primacy*). Instead, it sets a "modern standard for corporate responsibility" that commits firms to act to the benefit of *all* stakeholders (Business Roundtable, 2019). In other words, this new paradigm allows managers to invest in socially responsible initiatives, even if this may come at the expense of shareholders.

A key stakeholder of a company is the government, which provides the firm and society as a whole with necessary infrastructure and levies taxes in return. Paying corporate taxes is thus inseparably linked to the concept of corporate social performance (CSP) in that tax payments can be regarded as an act of corporate social responsibility (CSR), i.e., a form of contributing business resources to the improvement of societal well-being (Nickerson et al., 2022). Avoiding taxes, in turn, can be seen as an act of corporate social *ir*-responsibility (CSI), which is broadly defined as all entrepreneurial activity that "negatively affects an identifiable social stakeholder's legitimate claims" (Strike, Gao, and Bansal, 2006, p. 851).[1]

Previous literature on the relationship between tax payments and the broader concept of CSP has not been conclusive and it is not clear whether firms view CSR initiatives as substitutes for tax payments or if they see CSR activities and tax payments as complementing each other in showing good citizenship (e.g., Davis et al., 2016; Kim, Park, and Wier, 2012; Mayberry and Watson, 2021). Empirical research exists with regard to the firm performance implications of CSP and tax avoidance, respectively (e.g., Gallemore, Maydew, and Thornock, 2014; Hanlon and

[1] In this study, I use the terms *CSI*, *negative CSR*, and *ESG concern* (short for Environmental, Social, Governance) interchangeably to refer to corporate misdeeds as defined by Strike, Gao, and Bansal (2006). CSP is considered to capture the performance outcome of the entirety of a firm's corporate social actions on the continuum from socially responsible (CSR) to irresponsible (CSI) activities.

Slemrod, 2009; Kang, Germann, and Grewal, 2016), but prior literature has not yet examined how the concepts interact with each other. This research aims to fill this void and specifically addresses the question whether refraining from tax avoidance can mitigate the negative consequences of showing a poor CSP in other non-tax related areas. To answer this question, I compile an annual panel data set comprising 392 firms from the Fortune 500 list (i.e., the largest US based corporations in terms of total revenue) between 2003 and 2013. I estimate a fixed effects panel regression model using Tobin's Q, a market based measure of firm performance, as dependent variable. I use measures for CSR and CSI activity of firms derived from the *MSCI ESG Ratings* data set as well as their cash effective tax rate (ETR) as a measure for (inverse) tax aggressiveness and a set of control variables established in previous literature as independent variables. Contrary to expectations, I find negative effects of CSR on firm performance in my sample. In the discussion of the results, I attempt to shed some light on the reasons for these unexpected results.

With respect to CSI and tax avoidance, on the other hand, my findings conform with my ex ante expectations: I find CSI to have the negative effect on firm performance that has been documented in prior literature and I can show that this negative effect is positively moderated by the cash ETR. This implies that a less aggressive tax behavior as expressed by a higher cash ETR (i.e., higher tax payments relative to a firm's profits) can mitigate the negative consequences of engaging in other types of socially irresponsible behavior.

With these results, this study sheds new light on how CSR, CSI, and tax avoidance are interrelated and, to my knowledge, it is the first one to examine their joint impact on firm performance. The evidence from this study first of all supports the widely held view that investors care if a company behaves irresponsibly, and it implies that managers are well advised to avoid such CSI incidents. If a firm is nevertheless involved in a CSI incident, my results suggest that a less aggressive tax behavior (i.e., a tax policy that refrains from aggressive tax avoidance) can mitigate the negative consequences. From a methodological perspective, I show, using the example of tax avoidance, that it can be beneficial to decompose the multi-faceted constructs of CSI and CSR into their sub-components in empirical analyses rather than considering them as a whole. Distinct types of corporate (mis-)conduct can potentially have a very different impact on corporate success and breaking it down into sub-components possibly allows to answer more nuanced research questions pertaining to the interrelation between behaviors in different fields of corporate activity.

The remainder of this study is organized as follows: First, I summarize relevant strands of literature. Then, I present conceptual and theoretical considerations that lead to my research hypotheses. Following that, I describe my data set and outline my modeling approach. Finally, I present and discuss the results of my analyses and I conclude with the implications of the study.

3.2 Literature

Previous literature provides research on the impact of tax avoidance on firm financial performance as well as research that investigates the impact of socially irresponsible behavior in a broader sense. In the latter stream of literature, tax avoidance is often implicitly considered as one dimension of CSI.[2] A third strand of research has considered tax behavior and CSP jointly, however only investigating the relation between the two and not the joint impact of CSP and tax behavior on firm financial performance. The goal of this study is therefore to address this void by analyzing the firm performance implications of tax avoidance and CSP as well as the moderating effect of tax payments on the relation between CSI and firm performance. In the remainder of this chapter, I outline relevant findings in all three aforementioned literature streams.

3.2.1 Tax avoidance and firm financial performance

Empirical evidence as to whether and how corporate tax avoidance impacts a firm's financial performance is inconclusive. I introduced the state of the literature regarding the link between tax payments and firm performance at length in Section 2.2 and I recapitulate the main aspects subsequently. For a tabular overview of relevant literature on this relation, please refer to Table 2.1. If tax avoidance was entirely costless to firms, then the effect of tax avoidance on a firm's financial performance would be trivial: a reduction in the tax burden would increase bottom line returns (Desai and Dharmapala, 2009). However, prior literature has identified various dimensions of (non-tax) costs that are linked to tax avoidance activities and that can potentially offset the benefits of reduced tax payments (e.g., reputational costs (Hardeck and Hertl, 2014) or costs due to an increased scrutiny by tax authorities after a revelation of a tax shelter involve-

[2]The MSCI ESG Ratings data set (formerly known as *KLD Stats* database) is the most frequently used data source for third-party CSR scores in academic literature, and it records tax avoidance incidents in an item named "tax disputes". As such, it is mostly integrated into an aggregate measure of ESG concerns. Note: I henceforth refer to the data set by its new name MSCI ESG Ratings.

ment (Dyreng, Hoopes, and Wilde, 2016)). As a result, the net effect is much more nuanced than the naive view might suggest and the direction is a priori unclear. Desai and Dharmapala (2009) study a year-level panel data set of over 800 US firms between 1993 and 2001. Using the book-tax gap as a measure for tax aggressiveness and Tobin's Q to proxy for firm performance, the authors find no significant effects in their study. Hanlon and Slemrod (2009), on the other hand, find a negative stock market reaction to the first press mention of a firm's involvement in a tax shelter. In their event study, they find that this negative effect is more pronounced for firms from the retail sector. This result suggests that a firm's degree of exposure to the consumer may be a moderating factor that helps explain whether for a given firm tax avoidance is beneficial or harmful. The authors attribute this result at least partially to reputational costs, which seem to be higher for B2C rather than B2B firms. What is more, Hanlon and Slemrod (2009) show that a higher effective tax rate (ETR) can alleviate the negative impact of news about tax shelter involvement. Gallemore, Maydew, and Thornock (2014) replicate the core findings by Hanlon and Slemrod (2009) with a larger sample of firms and tax avoidance incidents. In supplementary analyses, Gallemore, Maydew, and Thornock (2014) extend the event window from three days to 30 days. They find that after a month, the negative stock market reaction returns to zero, indicating that it is only short-term. The lab study by Hardeck, Harden, and Upton (2019) also points at reputational costs playing a role in that it shows that consumers' willingness-to-pay decreases once they learn about a firm's aggressive tax planning. Blaufus, Möhlmann, and Schwäbe (2019) distinguish in their event study between (legal) tax avoidance and (illegal) tax evasion news and conclude that stock market effects are negative for (illegal) tax evasion activities, whereas they are positive for (legal) tax avoidance news. With only 176 news items, however, the scope of this study is rather limited as news items were coded manually with respect to the legality of the described tax avoidance incident. In Chapter 2, this thesis also contributes to this stream of research and finds weak evidence that, on average, investors negatively value an increase in the tax payments. However, the coefficient is rather small and subject to considerable uncertainty. With respect to (social) media attention towards firms' tax behaviors, the results of Chapter 2 indicate that stock returns are not affected, yet investor behavior still changes such that the overall trading volume and idiosyncratic risk of a firm's stock increase once the volume and/or negativity of media reporting increases.

Instead of directly analyzing the effect of tax avoidance on measures of firm performance, other studies have also tried to investigate whether and how firms change their tax behavior following media attention (e.g., Chen, Schuchard, and Stomberg, 2019; Dwenger and Treber, 2022; Dyreng, Hoopes, and Wilde, 2016). These studies argue that firms likely receive increased scrutiny by tax authorities and the public after they were once associated with tax avoidance. This increases the costs that managers face when trying to conceal any subsequent tax avoidance activities from the public (Desai and Dharmapala, 2009), and a consequence might be a reduction in tax aggressiveness. While Chen, Schuchard, and Stomberg (2019) do not find evidence for firms reducing their tax aggressiveness following increased media attention, results from a quasi-experiment by Dwenger and Treber (2022) point to a different direction. The introduction of a naming-and-shaming policy in Slovenia in 2012 led to a substantial reduction in firms' tax debts, indicating the presence of reputational risks, at least in the perception of managers. Dyreng, Hoopes, and Wilde (2016) document that negative public scrutiny of tax avoidance activities exerted by external activist groups has a significant impact on the behavior of publicly listed companies. The authors show that firms affected by an exogenous shock to the disclosure regulations of UK firms reduced their corporate activities in tax haven countries and increased their tax expenses subsequently. In summary, it is not conclusively clear how tax behavior in general affects firm performance and this is also not be the focus of this study. Instead, this study aims to contribute to the literature by considering the as yet unexplored moderating effect of tax behavior in the relationship between CSI and firm performance.

3.2.2 Corporate social performance and firm financial performance

Literature has broadly defined corporate social responsibility as the contribution of business resources to the improvement of societal well-being (e.g., Nickerson et al., 2022). What specifically can and cannot be considered a CSR measure, however, is often subject to the interpretation of the companies involved, who frequently and readily communicate their socially responsible actions to the public. Since there is no standardized and mandatory disclosure format yet for CSR activities (as is the case, e.g., in the reporting of a firm's financial position with accounting standards such as IFRS or GAAP), CSR literature has (besides survey and experimental data) mostly relied on social ratings provided by rating agencies to get as close as possible to an objective assessment of a firm's CSP (e.g., Jayachandran, Kalaignanam, and Eilert, 2013; Kang, Germann, and Grewal, 2016; Mishra and Modi, 2016). Meta-analytic studies by Orlitzky, Schmidt, and Rynes (2003) and Margolis, Elfenbein, and Walsh (2009) have systematically reviewed the (at the time) existing body of literature in the field. Orlitzky, Schmidt, and Rynes (2003) document a clear positive association between the social and financial performance of a firm and conclude that social responsibility and shareholder wealth maximization are not necessarily inconsistent with one another. Margolis, Elfenbein, and Walsh (2009) also find a positive effect on average, yet the authors are more cautious in their interpretation and describe the effect as being rather small. For socially irresponsible misdeeds, however, they find more pronounced (negative) effects on financial performance, supporting the notion that doing bad hurts more than doing good helps. They further report that 28 percent of the investigated effects in their sample were positive, two percent were negative, and a considerable 59 percent were not significant. The substantial share of insignificant results is likely driven by the fact that there is a large degree of heterogeneity in CSR effectiveness across different CSR dimensions, across firm and industry characteristics, and with respect to the timing of CSR initiatives. I provide an overview over articles that identify constraints and moderators to the CSR-firm performance relation in Table 3.1.

For example, Servaes and Tamayo (2013) identify customer awareness as a seemingly obvious, yet crucial, necessary condition for CSR to impact firm performance. Using advertising intensity to proxy for the public's awareness of a given firm, Servaes and Tamayo (2013) show that the effect of CSR activities on firm performance is positively moderated by the firm's customer awareness. They further show that this effect reverses for firms who have a poor reputation as corporate citizen. This latter finding is closely related to a study by Becker-Olsen, Cudmore, and Hill (2006), who show in an experimental setting that the perceived fit, i.e., the link between the goal of a CSR initiative and the firm's overall perception, positively moderates the CSR-firm performance relation. They further show that, regarding the timing of an initiative, proactive CSR activities are more promising than reactive ones. Kang, Germann, and Grewal (2016, pp. 59-60) also examine the temporal dimension of CSR activities and find evidence for the "good management mechanism", i.e., that firm performance actually results from investments in CSR and not vice versa. They find that CSR often trails CSI, but that these reactive CSR initiatives that merely aim to compensate for past irresponsible actions (referred to by the authors as the "penance mechanism") are ineffective.

A more recent study by Nickerson et al. (2022) classifies CSR actions on an accountability dimension into *corrective* (i.e., addressing negative externalities by changing own business operations), *compensating* (i.e., addressing negative externalities *without* changing own business operations), and *cultivating goodwill* CSR (i.e, supporting good causes unrelated to own busi-

Table 3.1: Literature (CSP and financial performance)

Study	**Dependent variable**	**CSR data**	**Constraints to CSR effectiveness**	**Main finding**
Becker-Olsen, Cudmore, and Hill (2006)	Attitude towards firm & purchase intention	Survey data	Fit & timing (proactive vs. reactive)	Proactive CSR activities that have a high fit with the focal firm are the most promising ones
Servaes and Tamayo (2013)	Tobin's Q	MSCI ESG Ratings	Customer awareness & reputation	CSR is more effective if firms' customer awareness is high; effect reverses for firms with poor CSR reputation
Kang, Germann, and Grewal (2016)	Tobin's Q	MSCI ESG Ratings	Timing of CSI and CSR	Reactive CSR initiatives that aim at compensating for CSI are ineffective
Nickerson et al. (2022)	Brand sales	CSR announcements (`CSRwire.com`)	Accountability of CSR (*corrective*, *compensating*, & *cultivating*)	CSR actions that (do not) address the firm's negative externalities have a positive (negative) effect on sales
This study	Tobin's Q	MSCI ESG Ratings	Cash ETR	CSI negatively affects firm performance, yet less so if tax payments are high; CSR has negative effect on performance of large-cap firms with high share of institutional investors

ETR: effective tax rate · CSR: corporate social responsibility · CSI: corporate social irresponsibility ness operations). The authors find positive effects on sales only for actions that take accountability for negative externalities (i.e., for compensating and corrective CSR), whereas they even find negative effects for unrelated philanthropic CSR. This research contributes to this literature stream by showing that a firm's ETR, i.e., the amount of taxes payed relative to pre-tax profits, positively moderates the negative effects of CSI on firm financial performance. Moreover, in my post-hoc analyses, I show that market capitalization and the share of institutional ownership appear to be important determinants of CSR effectiveness. Specifically, large-cap firms with a high share of non-retail owners are negatively affected by investments in CSR.

3.2.3 Corporate social performance and tax avoidance

Much of the literature on CSP tends to implicitly consider tax avoidance as a facet of CSI in that it integrates tax avoidance incidents into aggregate measures of CSI (e.g., Kang, Germann, and Grewal, 2016; Kotchen and Moon, 2012; Servaes and Tamayo, 2013). Only a small number of studies is explicitly dedicated to empirically assess the relation between a firm's CSP and its tax behavior, and the results are inconclusive. I provide an overview of this literature stream in Table 3.2. Most studies in this field refrain from making strong causal claims and attempt to answer whether firms who act more socially responsible are associated with a lower tax aggressiveness (i.e., whether they are also less likely to avoid taxes).

With the natural experiment by Mayberry and Watson (2021), I am only aware of one study that phrases a clear cause-and-effect relationship, yet the authors find no empirical evidence in their data that CSR affects the degree of tax avoidance. Three plausible hypotheses have evolved around the question how CSR and tax avoidance are related. Mayberry and Watson (2021) refer to these hypotheses as *transparent reporting*, *opportunistic reporting*, and *decoupling* hypothesis, respectively, and there is support in prior literature for all three of them. First, it might be that firms' tax aggressiveness and CSR activities are negatively related as high levels of tax avoidance would undermine the credibility of CSR engagement. Studies by Kim, Park, and Wier (2012), Lanis and Richardson (2012), and Hoi, Wu, and Zhang (2013) document negative associations between different measures of tax avoidance (or earnings management in general in the case of Kim, Park, and Wier (2012)) and CSR and understand this as evidence for the transparent reporting hypothesis.

Table 3.2: Literature (CSR and tax avoidance)

Study	Main finding	Sample	CSR measure	TA measure	Aggregation
Kim, Park, and Wier (2012)	CSR $\xrightarrow{-}$ TA	US firms excl. finance (1991-2009); ~18k obs.	MSCI ESG Ratings	Discretionary accruals, real activities manipulation, & SEC investigations after GAAP violations	annual
Lanis and Richardson (2012)	CSR $\xrightarrow{-}$ TA	408 Australian firms (excl. finance) in the FY 2008/09 (cross-section)	References to 52 CSR activity items in annual reports	GAAP ETR	annual
Hoi, Wu, and Zhang (2013)	CSR $\xrightarrow{-}$ TA	US firms excl. utilities/finance (2003-2009); ~11k obs.	MSCI ESG Ratings	Book-tax gap, Cash ETR, & latent sheltering probability to capture extremely aggressive TA	annual
Davis et al. (2016)	CSR $\xrightarrow{+}$ TA	US firms (2006-2011); ~6k obs.	MSCI ESG Ratings	Cash ETR & tax lobbying expenditures	annual
Mayberry and Watson (2021)	CSR $\xrightarrow{0}$ TA	large US firms excl. utilities/finance (1987-2010); ~60k obs.	Quasi-experimental treatment: state-level changes in constituency laws	GAAP ETR & Cash ETR	annual

CSR: corporate social responsibility · TA: tax avoidance · GAAP: US Generally Accepted Accounting Principles · ETR: effective tax rate · FY: fiscal year

Based on their findings, Hoi, Wu, and Zhang (2013) argue that engagement in CSR is part of a general corporate culture rather than being spurred by opportunistic motives. Davis et al. (2016), in contrast, find a positive relation between CSR and tax avoidance in support of the opportunistic reporting hypothesis, suggesting that tax payments and CSR are substitutes rather than complements. Davis et al. (2016) explain their deviating results from Hoi, Wu, and Zhang (2013) with differences in the study designs: First, Hoi, Wu, and Zhang (2013) focus on a subset of firms with a poor CSR rating. Second, Hoi, Wu, and Zhang (2013) focus on tax avoidance practices that are on the more extreme end of the continuum. Davis et al. (2016), on the other hand, take a wider perspective and consider a broad spectrum of legal tax avoidance practices.

While all of the aforementioned studies make only correlational claims about *associations* (and not causal relations) between the constructs, I am aware of only one study (Mayberry and Watson, 2021) whose design, according to the authors, establishes a causal relationship. Mayberry and Watson (2021) use enactments of state-level constituency statutes as quasi-random treatment in a natural experiment. While US law traditionally used to mandate managers to maximize shareholder value, more and more US states introduced constituency statutes since the late 1980s that allow or require managers to also consider interests of stakeholders other than shareholders in their actions. This, the authors argue, represents an exogenous reduction in the costs for managers of engaging in CSR activities. The study does not find any evidence, that the quasi-experimental treatment to CSR costs changes subsequent tax behavior of firms, which is consistent with the decoupling hypothesis.

3.3 Theory and Hypotheses

Rational investors assess and eventually update a company's valuation based on all relevant and observable information in the market (Fama, 1970). Prior research has established that investors are particularly concerned with information regarding corporate actions that affect stakeholder relationships (Groening, Mittal, and Zhang, 2016). An example for such an activity that affects stakeholder relationships is the engagement in CSR activities, as it caters the longer-term interests of a broad set of non-investor stakeholders (e.g., employees, consumers, governments, the society as a whole, etc.). On the other hand, it can potentially come at the expense of shareholders in the short term (Moser and Martin, 2012). Thus, CSR can influence company valuation in two ways: First, a CSR activity can be a positive signal to investors in that it strengthens stakeholder relations. This would imply a firm performance enhancing effect of CSR (Groening, Mittal, and Zhang, 2016). Second, CSR might also lead to adverse investor reactions as CSR is typically associated with immediate costs that can potentially exceed the benefits to the firm. These competing mechanisms lead to a trade-off, where an investor has to decide whether she expects the benefits of a CSR measure to outweigh the costs or not. As discussed in Section 3.2.1, investors on average seem to value the benefits higher than the costs, resulting in predominantly positive outcomes of CSR in prior literature (for literature on constraints to CSR effectiveness, see Table 3.1). CSR has been found to positively affect not only firm value (e.g., Kang, Germann, and Grewal, 2016), but also consumers' brand attitudes (e.g., Ailawadi et al., 2014; Du, Bhattacharya, and Sen, 2007) and purchase behavior (e.g., Nickerson et al., 2022).

Regarding the effects of socially *irresponsible* actions, the above logic can be only partially reversed: CSI actions, if made public, can harm firm performance through weakened stakeholder relations. On the other hand, CSI only sometimes (yet not always) goes along with cost savings, which in turn can enhance shareholder value. The types of savings are as multifaceted as the CSI activities themselves: for example, violations of labor rights often come along with savings in wages from the perspective of the firm, product safety or quality concerns may be associated with manufacturing inferior and cheaper materials, and producing in countries without environmental standards can lower manufacturing costs. However, for other dimensions of CSI, cost savings are not as evident or simply non-existent (consider for example intransparency concerning a firm's political involvement or incidents of discrimination at the workplace). The resulting dominance of the disadvantages over the cost savings in the case of CSI might explain why there is consensus in previous literature that "doing bad" hurts firm value more than "doing good" helps (Margolis, Elfenbein, and Walsh, 2009, p. 23). For the specific case of tax avoidance, the direct cost savings are much more, and the potential costs less evident compared to other dimensions of CSI.

Consider, for example, a firm affected by an environmental CSI incident such as a spill on an oil rig. For one thing, it does not take much imagination on the part of an investor to realize the direct cost of repairing the damage caused. In addition, the reputational costs that manifest themselves through consumer backlash are likely to be rather high, as images of an oil spill and birds dying in it are very tangible for consumers. In contrast, it is much harder for consumers to see how an aggressive tax policy of a firm affects them personally, as this is a very intangible construct. Investors might anticipate this consumer reaction and weigh the costs of tax avoidance less heavily than those of other types of CSI, which would be reflected in different firm value implications. To identify these sorts of heterogeneous effects of different forms of CSI on firm performance, I conclude that it is warranted to disentangle tax avoidance from non-tax CSI and not treat it as just another type of socially irresponsible behavior.

Regarding the antecedents and interplay of CSR, CSI, and firm performance, different temporal sequences are plausible, as Kang, Germann, and Grewal (2016) posit: First, the *good management mechanism* would imply that good firm performance results from the engagement in CSR activities (and the absence of CSI) (e.g., Jayachandran, Kalaignanam, and Eilert, 2013). Second, the *slack resources mechanism* suggests that investments in CSR are rather a consequence of good firm performance than vice versa, since it provides excess resources that can subsequently be given to social causes (e.g., McGuire, Sundgren, and Schneeweis, 1988). Third, the *insurance mechanism* states that firms engage in CSR to protect against negative consequences of subsequent CSI (e.g., Godfrey, Merrill, and Hansen, 2009). Fourth, the *penance mechanism* indicates that CSR trails preceding CSI to offset and compensate for negative consequences (e.g., Kotchen and Moon, 2012).[3] Kang, Germann, and Grewal (2016) systematically examine these four mechanisms and find support for the penance mechanism, i.e., that CSR activities are mostly a result from preceding CSI. Consistent with these findings and borrowing from the idea that consequences of CSI can be mitigated by CSR as a means of risk management (Hoi, Wu, and Zhang, 2013), I expect that *tax-related* CSR (i.e., not engaging in aggressive tax avoidance) should also mitigate the negative consequences of CSI.

Based on the theory provided above, I arrive at the following hypotheses, which I test in the following:

H1: Engagement in corporate social responsibility (CSR) activities positively affects firm performance.

H2: Engagement in corporate social irresponsibility (CSI) activities negatively affects firm performance.

H3: Higher tax payments (i.e., no or fewer engagement in tax avoidance) mitigate the negative consequences that CSI has on firm performance.

In Figure 3.1, I present my conceptual framework that corresponds to the theoretical considerations outlined above.

[3] For a more detailed description of the four mechanisms and an overview of corresponding literature, see Kang, Germann, and Grewal (2016).

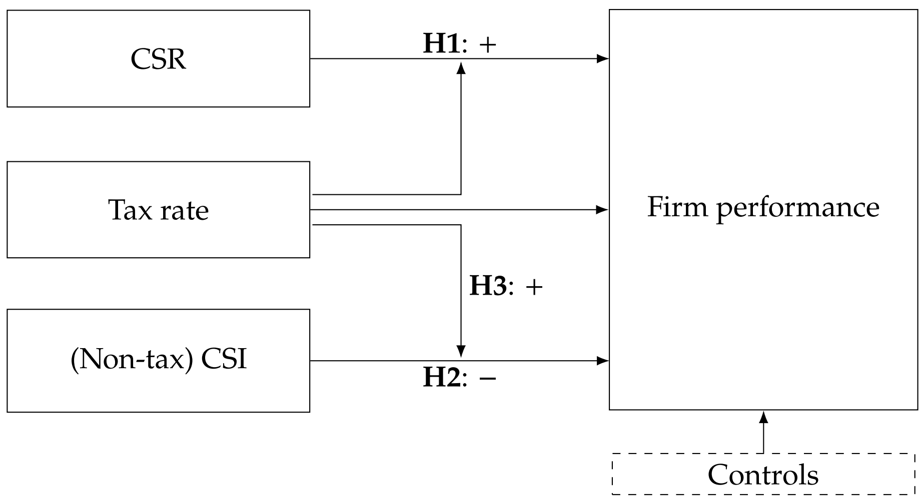


Figure 3.1: Conceptual framework and expected effects

3.4 Data

I perform my analyses on a data set comprising the publicly listed firms that were part of the 2018 Fortune 500 list of the largest US-based companies by revenue. I collect firm financial data from *Thomson Reuters Datastream* and I rely on corporate social (ir-)responsibility scores provided by the financial services provider *MSCI* in their commercial MSCI ESG Ratings data set. The observation period is between 2003 and 2013 and my full sample covers 3,436 firm-year observations.

3.4.1 Firm financial data

The intersection of the Thomson Reuters data and the MSCI ESG Ratings data results in a sample of 3,436 firm-year observations that form the basis of my analyses. Following previous literature, I compute year-end measures of Tobin's Q using the method originally suggested by Chung and Pruitt (1994) and for example applied in the research by Kang, Germann, and Grewal (2016) or Jayachandran, Kalaignanam, and Eilert (2013). Being defined as the ratio of a firm's market value divided by the replacement value of its assets, Tobin's Q expresses how much value the company can create at the stock market given its asset base (Servaes and Tamayo, 2013). As a market based measure, Tobin's Q is considered a long-term indicator for investors' expectations of the firm's future earnings (Kang, Germann, and Grewal, 2016) and should therefore reasonably well capture investor responses to a firm's social performance. In my sample of 3,436 firm-years, the average firm has a Tobin's Q value of 1.28 and values range from 0.03 to

12.72. One of the focal constructs in this study is the tax aggressiveness of a firm. To measure (inverse) tax aggressiveness, I use a firm's cash ETR as independent variable. Analogously to the procedure in Section 2.4, I compute it as the ratio of cash taxes paid to the pre-tax income less extraordinary items in the same period. Again, I winsorize at 0 and 50 percent as proposed by Hanlon and Slemrod (2009) to avoid extreme outliers. I further collect data for the financial leverage (i.e., the debt-to-equity ratio times 100), for a firm's current period profitability as measured by the return on assets (ROA; computed as the net income divided by total assets times 100), and for firm size as measured by the number of employees. I present summary statistics in Table 3.3 and pairwise correlations in Table 3.4.

Table 3.3: Descriptive statistics

	N	Min.	$Q_{0.25}$	Median	Mean	$Q_{0.75}$	Max.	SD
Firm financial variables								
$Tobins\_Q_{i,t}$	3,436	0.026	0.532	0.930	1.278	1.649	12.719	1.177
$CashETR_{i,t}$	3,436	0.000	0.142	0.256	0.247	0.343	0.500	0.139
$ROA_{i,t}$	3,436	-15.286	2.822	5.507	6.598	9.372	39.121	5.102
$Leverage_{i,t}$	3,436	0.000	10.832	22.066	24.225	35.234	103.045	16.935
$Employees_{i,t}$	3,436	51	10,000	24,696.500	55,721.939	53,325	2,200,000	131,889.807
Corporate social (ir-)responsibility variables								
$SumStrengths_{i,t}$	3,436	0	1	3	4.103	6	22	4.076
$SumConcerns_{i,t}$	3,436	0	1	3	3.248	4	18	2.788
$NetCSR_{i,t}$	3,436	-11	-2	0	0.855	3	19	4.101
$CSR_{i,t}$	3,436	-1.102	-0.658	-0.110	0.172	0.815	5.355	1.061
$CSI_{i,t}$	3,436	-1.498	-0.684	-0.129	0.084	0.610	9.226	1.077

Table 3.4: Pairwise Pearson correlation coefficients

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	$Tobins\_Q$	1								
(2)	$CashETR$	0.003	1							
(3)	ROA	0.659	0.068	1						
(4)	$Leverage$	-0.202	-0.080	-0.209	1					
(5)	$Employees$	0.020	0.053	0.060	0.045	1				
(6)	CSR	0.088	-0.053	0.110	0.001	0.279	1			
(7)	CSI	-0.082	-0.016	-0.030	0.126	0.398	0.431	1		
(8)	$SumStrengths$	0.054	-0.064	0.110	0	0.279	0.951	0.384	1	
(9)	$SumConcerns$	-0.100	0.007	-0.022	0.108	0.372	0.326	0.865	0.333	1

3.4.2 Corporate social (ir-)responsibility data

Like most of the academic literature that relies on third-party ratings of firms' CSR and CSI activities, I also use the MSCI ESG Ratings data set (formerly known as *KLD Stats* database) for my analyses. As a global financial services provider, MSCI operates several stock indeces, some of which have a focus on sustainable investment.[4] The MSCI ESG Ratings are the basis on which MSCI selects constituents of their socially responsible indeces. MSCI uses public information from a variety of sources such as company disclosures, global and local media outlets, as well as governments and NGOs, to evaluate firms along the dimensions corporate governance, community, diversity, employee relations, environment, and product. Each of these dimensions includes a number of indicators, each labeled as either strength or concern. I present an overview of the individual strength and concern indicators in Table 3.5.

Note that the listed indicators are not mutually exclusive since over time they eventually undergo definitional changes, some are deprecated and new ones are introduced (e.g., the environmental concern indicator *Hazardous Waste* was deprecated in 2009 and from 2010 onwards covered by the indicator *Toxic Emissions and Waste*). Yet in one given year, indicators in fact are mutually exclusive and every CSR/CSI incident can be unambiguously attributed to one indicator. MSCI tracks five more indicators (namely business involvements related to alcohol, gambling, military contracting, nuclear power, or tobacco) that they regard as exclusion criteria for the composition of their social indeces (i.e., having a negative record in one of these categories inhibits the inclusion of a firm in a social stock index irrespective of the scores in all other categories).

I follow Kim, Park, and Wier (2012), who argue that these exclusionary indicators should not be included in the construction of a CSR score because these dimensions do not concern firms' discretionary activities (i.e., whether or not a company is involved in the tobacco industry, for example, is not a discretionary decision that concerns their corporate social performance). As one goal of this study pertains to examining the moderating role of tax payments in the relation between CSI and firm performance, I further exclude the indicator "tax disputes" (classified

[4]For instance, the *MSCI KLD 400 Social Index*, according to the corresponding fact sheet, is "*designed to provide exposure to companies with high MSCI ESG Ratings while excluding companies whose products may have negative social or environmental impacts.*"; from: https://www.msci.com/our-solutions/indexes/esg-indexes (last access: April 11, 2023)

Table 3.5: ESG dimensions and strength/concern indicators

Corporate governance			
Strengths		*Concerns*	
Limited Compensation	Public Policy Strength	High Compensation	Political Accountability
Ownership Strength	Corruption & Instability	Tax Disputes	Public Policy Concern
Reporting Quality	Financial System Risk	Ownership Concern	Controversial Investments
Political Accountability		Accounting Concern	Governance Structures
		Reporting Quality	Bribery & Fraud
Community			
Strengths		*Concerns*	
Charitable Giving	Non-US Charitable Giving	Investment Controversies	Tax Disputes
Innovative Giving	Volunteer Programs	Impact on Local Communities	Indigenous Peoples Relations
Support for Housing	Community Engagement		
Support for Education	Indigenous Peoples Relations		
Diversity			
Strengths		*Concerns*	
CEO	Women & Minority Contracting	Discrimination	Board Diversity
Representation	Employment of the Underrepresented	Representation	Workforce Diversity
Board Diversity	Gay/Lesbian Policies		
Work/Life Benefits			
Employee relations			
Strengths		*Concerns*	
Union Relations	Compensation & Benefits	Collective Bargaining & Unions	Supply Chain Labor Standards
No Layoff Policy	Employee Relations	Health & Safety	Child Labor
Cash Profit Sharing	Professional Development	Workforce Reductions	Labor Management Relations
Strong Retirement Benefits	Human Capital Development	Pension/Benefits Concern	
Health & Safety	Labor Management		
Supply Chain Labor Standards	Controversial Sourcing		
Involvement			
Environment			
Strengths		*Concerns*	
Environmental Opportunities	Pollution & Waste	Hazardous Waste	Regulatory Compliance
Climate Change Vulnerability	Carbon Emissions	Ozone Depleting Chemicals	Toxic Emissions and Waste
Communications	Property, Plant, & Equipment	Agricultural Chemicals	Energy & Climate Change
Environmental Management Systems	Natural Capital	Impact of Products & Services	Biodiversity & Land Use
Financing Environmental Impact	Product Carbon Footprint	Operational Waste	Supply Chain Management
Energy Efficiency		Water Stress	
Product			
Strengths		*Concerns*	
Product Safety & Quality	R&D/Innovation	Product Safety & Quality	Marketing & Advertising
Social Opportunities	Product Safety	Anticompetitive Practices	Customer Relations
		Privacy & Data Security	

Note: Indicators are not free of overlap due to redefinitions of existing indicators, as well as discontinuations of old and initiations of new indicators over time.

as community concern until 2009 and as corporate governance concern thereafter) from the analyses. This allows me to disentangle tax aggressiveness from other types of CSI.

As stated above, there are frequent discontinuations of existing and introductions of new indicators from year to year, which is why the total number of strengths and concerns indicators varies, as can be seen in Figure 3.2. What is more, coverage of the Fortune 500 firms is not constant over time, yielding an unbalanced panel. Specifically, between the years 2002 and 2003, there was a substantial increase in firm coverage (see Appendix B.1), which is why I choose the year 2003 as the start of the observation period. The year 2013 is the last year with complete data availability and marks the end of my observation period. The MSCI ESG Ratings data set

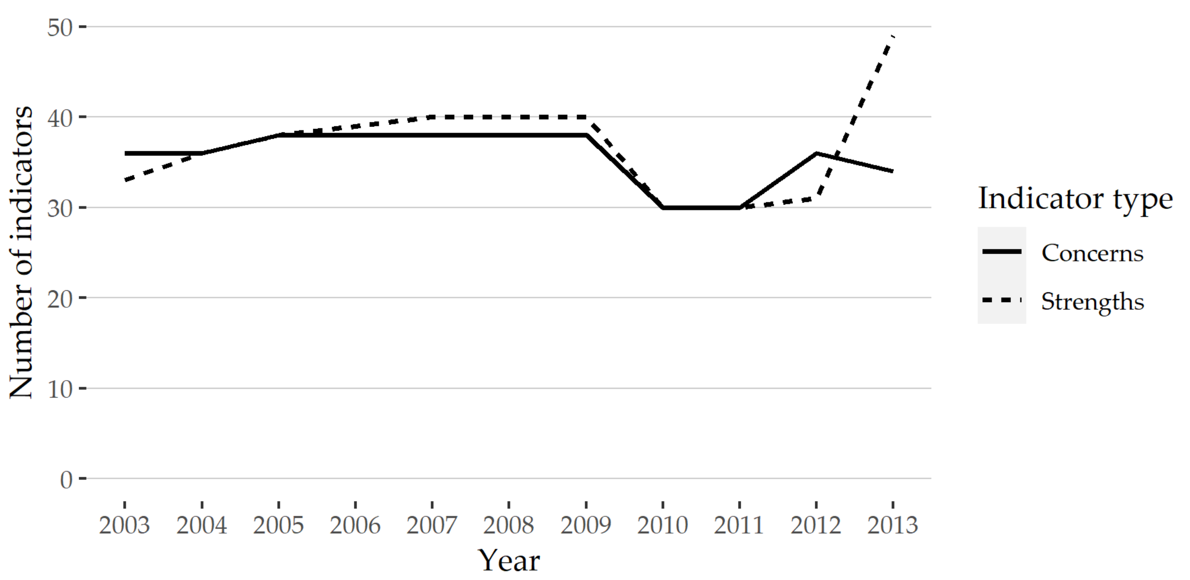


Figure 3.2: Number of ESG indicators over time

was subject to some criticism in the past (e.g., Kang, Germann, and Grewal, 2016; Kotchen and Moon, 2012; Mattingly and Berman, 2006) that was mainly directed at the way in which it was used in previous literature. The standard approach through the 2010s and even beyond was to simply add up all the strengths and subtract the concerns of a firm in a given year, yielding an aggregated net ESG score (although only used for robustness checks, I report the raw sums of strengths and concerns in Table 3.3 as $SumStrengths_{i,t}$ and $SumConcerns_{i,t}$, respectively, and the naive net score as $NetCSR_{i,t}$ for the sake of completeness). The implicit assumption that this procedure brings along is that one strength can exactly compensate for one concern and that, when using this score as independent variable in a regression, reactions in the dependent variable to strengths and concerns are symmetric by definition.

Not only due to the fact that my research hypotheses require a separate consideration of CSI, but also in view of the theoretical and empirical findings on asymmetric responses to CSR and CSI (e.g., Sen and Bhattacharya, 2001; Margolis, Elfenbein, and Walsh, 2009), it seems warranted to consider CSR and CSI as two distinct constructs. I do this in accordance with the approach proposed by Kotchen and Moon (2012) and Kang, Germann, and Grewal (2016), who suggest to first sum up strengths and concerns of a given firm i in year t across all dimensions, and to then compute standardized Z-scores for CSR and CSI as follows:

$$CSR_{i,t} = \frac{SumStrengths_{i,t} - \overline{SumStrengths_t}}{sd(SumStrengths_t)} \tag{3.1}$$

$$CSI_{i,t} = \frac{SumConcerns_{i,t} - \overline{SumConcerns_t}}{sd(SumConcerns_t)} \tag{3.2}$$

where $CSR_{i,t}$ ($CSI_{i,t}$) represents the standardized Z-score for the sum of firm i's ESG strengths (concerns) in year t, $\overline{SumStrengths_t}$ ($\overline{SumConcerns_t}$) is the average score and $sd(SumStrengths_t)$ ($sd(SumConcerns_t)$) the standard deviation of the strengths (concerns) across all firms in year t. To give an intuition of how strengths and concerns develop over time for individual firms, I provide further descriptive graphics in Figure 3.3. Panel A (B) of the graphic shows the development of ESG strengths (concerns) for individual firms over time. As per eyeballing, the sum of strengths appears to be slightly increasing over time, on average, whereas the sum of concerns slightly reduces (note that the depicted graphic does *not* standardize for different numbers of indicators over different years). This model-free observation is in line with the notion that firms are increasingly aware of social issues and are increasing their engagement in CSR initiatives.

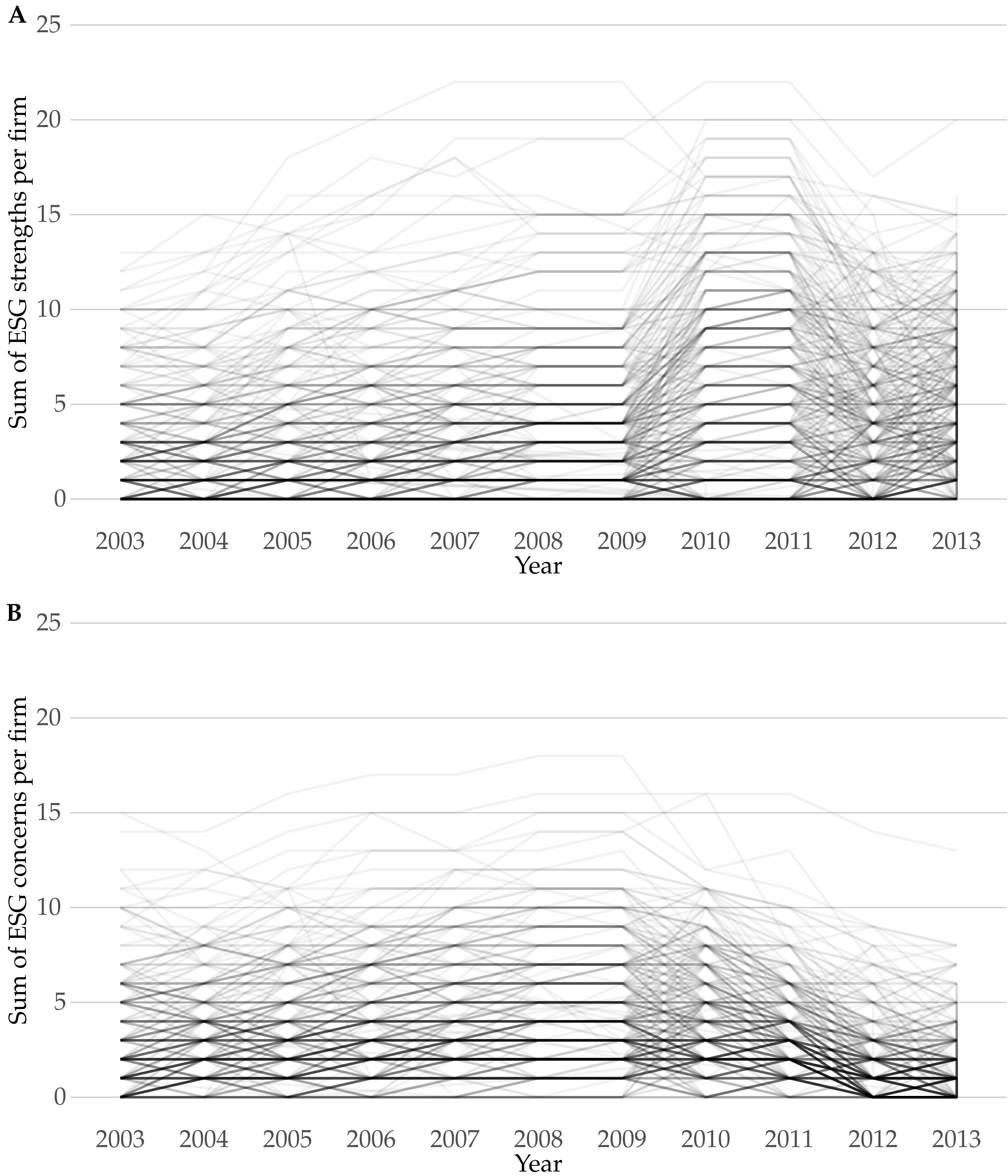


Figure 3.3: ESG strengths (Panel A) and concerns (Panel B) per firm over time

3.5 Model

To test the hypotheses derived in Section 3.3, I estimate a panel data regression with firm and year fixed effects to account for heterogeneity across these dimensions. As recommended by Hirsch and Seaks (1993), I use the log-transformation of Tobin's Q as my dependent variable measuring firm performance and regress it on the annual CSR and CSI variables derived from the MSCI ESG Ratings data set, on the cash ETR, on the interactions between the cash ETRs and the CSR and the CSI scores, respectively, and on a set of control variables. In my focal specification, I operationalize CSR and CSI as the Z-scores CSR and CSI, respectively, using the approach suggested by Kang, Germann, and Grewal (2016) and Kotchen and Moon (2012). Following prior literature (e.g., Kang, Germann, and Grewal, 2016), I include as control variables the return on assets (ROA) as a measure for current profitability, financial leverage ($Leverage$) to measure the riskiness of a firm's financial position, and the log of the number of employees ($log(Employees)$) to proxy for the time-varying component of firm size. These factors likely influence both the CSR agenda of a firm and firm performance, and adjusting for them therefore reduces potential biases in the estimated effects of CSR and CSI on firm performance. I present the regression equation of my focal model in Equation 3.3:

$$\begin{aligned} log(Tobins\_Q)_{i,t} = \beta_0 + &\beta_1 * CSR_{i,t} + \beta_2 * CSI_{i,t} + \beta_3 * CashETR_{i,t} \\ &+ \beta_4 * CSI_{i,t} * CashETR_{i,t} + \beta_5 * CSR_{i,t} * CashETR_{i,t} \\ &+ \beta_6 * ROA_{i,t} + \beta_7 * Leverage_{i,t} + \beta_8 * log(Employees)_{i,t} \\ &+ \eta_i + \eta_t + \varepsilon_{i,t} \end{aligned} \tag{3.3}$$

with all variables as defined above, with the idiosyncratic error term denoted as $\varepsilon_{i,t}$, and with η_i and η_t being the firm and year fixed effects, respectively. I mean-center all numeric variables before computing the interactions. If my hypotheses derived in Section 3.3 effects hold, I would expect a positive sign for β_1 (hypothesis H1), a negative sign for β_2 (H2), and again a positive sign for the interaction coefficient β_4 (H3).

It is possible that not only current ESG strengths and weaknesses affect firm performance, but that past social activities also have an impact. Given the data structure at hand, it is not feasible to reliably disentangle the temporal structure of the events: all CSR and CSI scores are measures reported at the end of a calendar year and they contain activities that happen over the entire year. The firm financial data is reported by firms in their annual reports at the end of the fiscal year. If for a given firm I observe a concern regarding one ESG dimension, I cannot know whether this concern refers to an incident that took place a day before the publication of the annual report or maybe eleven months earlier.[5] While this may be a limitation to the presented study, I estimate a variant of the model introduced in Equation 3.3 that also includes one year lagged measures of CSR and CSI to support the validity of my results. I report the results of this robustness check in Appendix B.2.

As a further robustness check, I run all my analyses on three different samples. First, I use all 392 Fortune 500 firms (3,436 firm-year observations) for which I have data available. The models based on this full sample are my preferred specifications. On top of that, I create a sample that excludes 56 firms from the finance sector, leaving me with 2,986 firm-year observations. In doing so, I follow previous work from Hoi, Wu, and Zhang (2013) and Kim, Park, and Wier (2012), who argue that the characteristics of accruals differ for financial institutions compared to other firms. Finally, I run my analyses on a third sample that is composed by only those firms that primarily have a business-to-consumer (B2C) focus.[6] This follows from the observation that previous literature has found evidence that the financial consequences of socially (ir-)responsible behavior are more pronounced for consumer-oriented industries (e.g., Kotchen and Moon, 2012). In the following section, I show and discuss the results of my empirical analyses.

3.6 Results and Discussion

I present the results of my focal analyses in Table 3.6. Models (1) - (3) use the standardized CSR and CSI variables as suggested by Kang, Germann, and Grewal (2016) and Kotchen and Moon (2012) (CSR and CSI). While I think that this approach is clearly superior, I still estimate models using the more naive operationalization of simply adding up strengths and concerns (see, e.g., Bouquet and Deutsch, 2008; Griffin and Mahon, 1997; Hillman and Keim, 2001), respectively ($SumStrengths$ and $SumConcerns$). I report the corresponding results as robustness checks in Columns 4 - 6. Models 1 and 4 use the full sample of 392 firms. Models 2 and 3 use a sample

[5] Note that in cases where the fiscal year does not match the calendar year, I merge the data such that the overlap between fiscal and calendar year is maximized.

[6] Whether or not a company is considered a B2C company is the result of a rating by an independent person who is not the author of the study. The wording of the instruction can be found in Appendix B.3.

Table 3.6: Regression results

	Dependent Variable: $log(Tobins\_Q)$					
	(1)	(2)	(3)	(4)	(5)	(6)
CSR	-0.017 (0.011)	-0.023 (0.012)**	-0.003 (0.015)			
CSI	-0.018 (0.009)**	-0.028 (0.010)***	-0.016 (0.011)			
$CashETR * CSR$	0.021 (0.046)	0.033 (0.063)	-0.045 (0.072)			
$CashETR * CSI$	0.156 (0.045)***	0.102 (0.055)*	0.149 (0.062)**			
$SumStrengths$				-0.005 (0.003)*	-0.009 (0.003)***	-0.001 (0.004)
$SumConcerns$				-0.002 (0.004)	-0.005 (0.004)	-0.001 (0.005)
$CashETR * SumStrengths$				0.011 (0.011)	0.008 (0.014)	-0.005 (0.017)
$CashETR * SumConcerns$				0.049 (0.016)***	0.031 (0.018)*	0.055 (0.023)**
$CashETR$	-0.051 (0.046)	0.096 (0.055)*	0.101 (0.071)	-0.116 (0.051)**	0.056 (0.064)	0.040 (0.087)
ROA	0.037 (0.002)***	0.033 (0.002)***	0.041 (0.002)***	0.037 (0.002)***	0.033 (0.002)***	0.041 (0.002)***
$Leverage$	-0.003 (0.001)***	-0.007 (0.001)***	-0.001 (0.001)	-0.003 (0.001)***	-0.007 (0.001)***	-0.001 (0.001)
$log(Employees)$	-0.270 (0.018)***	-0.240 (0.019)***	-0.220 (0.024)***	-0.274 (0.019)***	-0.246 (0.019)***	-0.224 (0.024)***
N	3,436	2,986	1,877	3,436	2,986	1,877
Adj. R^2	0.900	0.870	0.918	0.900	0.869	0.918
Sample composition	Full	w/o Finance	B2C Focus	Full	w/o Finance	B2C Focus
Firm FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes

* p < .1, ** p < .05, *** p < .01

that excludes 56 firms from the finance sector, and the sample used in 4 and 6 only consists of 216 firms that primarily have a B2C focus. My first hypothesis concerns the effect of ESG strengths on firm performance, and based on the majority of previous literature, the expectation was that firm performance should improve as a result from involvement in CSR. Different to what I expected, this is not the case and I do not find support for hypothesis H1. On the contrary, I even find significantly negative effects in some of the models. I discuss potential explanations to this unexpected result later in this chapter. With regards to hypothesis H2, I find effects that conform with my expectations: involvement in socially irresponsible activities, i.e., an increase in ESG concerns, negatively affects firm performance, ceteris paribus. Specifically, an increase in the CSI score by one unit (which is equivalent to one standard deviation in the raw count variable) leads to a decrease in Tobin's Q of approximately 1.8 percent, ceteris paribus. This finding is largely in line with previous literature (e.g., Kang, Germann, and Grewal, 2016), and it emphasizes the importance for firms to refrain from socially irresponsible behavior. Next, I focus on the interaction between CSI (or $SumConcerns$) and $CashETR$ for which hypothesis H3 predicts a positive coefficient. Across all six specifications reported in Table 3.6, I find the hypothesized positive coefficient, which provides evidence in support of the notion that firms are able to mitigate the negative effect of CSI on firm performance by being compliant with the spirit of tax laws and by refraining from aggressive tax behavior.

With regards to hypotheses H2 and H3, my findings align with my expectations derived from prior literature. Involvement in socially irresponsible behavior harms firm performance as measured by Tobin's Q, i.e., the ratio of the market value of a firm's assets with their book value. Since Tobin's Q is a market-based measure for firm performance, we can say that, ceteris paribus, investors seem to penalize socially irresponsible behavior on the stock market. This is as expected and corresponds for example with findings by Kang, Germann, and Grewal (2016). The expected positive and significant interaction coefficient between CSI and the cash ETR of a firm supports hypothesis H3 stating that higher tax payments (i.e., a higher cash ETR) can alleviate the negative consequences that involvement in socially irresponsible activities has on firm performance.

Rather unexpected, on the other hand, are the results I find with respect to hypothesis H1. While the majority of prior literature finds positive effects of socially responsible activities on firm performance (see Section 3.2.2), I find insignificant or even weak negative effects in my model. This is certainly surprising, yet there are plausible arguments that can explain the effects that I find. What distinguishes my study design from most other existing research is the composition of the estimation sample. While I focus on a very selective set of 392 high-revenue companies, for example Kang, Germann, and Grewal (2016) and Servaes and Tamayo (2013), who find positive effects of CSR on firm performance, use much larger samples (Kang, Germann, and Grewal (2016) use about 4,500 firms, Servaes and Tamayo (2013) over 2,000). This implies that their universes of firms comprise not only large corporations, but also smaller firms that do not enter my analyses. Large-cap companies typically have a higher share of institutional investors (IR Magazine, 2021) and it has been established by previous literature that institutional investors have a shorter investment horizon than retail investors (Graves and Waddock, 1990). This short-term orientation of investors can lead to myopic management decisions (Mizik, 2010). Bushee (1998), for example, documents this in the context of investments in research and development (R&D) and shows that high levels of institutional ownership pressures managers into cutting long-term oriented R&D spendings to meet short-term earnings goals. A similar mechanism could be at work in the context of CSR investments and it might explain why I find negative investor reactions to CSR investments whereas studies analyzing on average smaller firms find the opposite.

To empirically support this reasoning, I conduct further robustness checks adding to my proposed model interaction terms of the CSR variable with (a) the share of institutional ownership $InstitOwn$ (Columns 1 - 3 of Table 3.7) and (b) the log market capitalization $log(MarketCap)$ (Columns 4 - 6 of Table 3.7). In line with the reasoning above, there is indeed weak evidence for a negative moderation effect of the share of institutional ownership on the effect of CSR on firm performance. This suggests that the larger the share of institutional (i.e., non-retail) investors in a stock, the more negative is the effect of investments in CSR on firm performance. However, the coefficients are small and come with substantial uncertainty, which may be caused by the fact, that within the sample of Fortune 500 firms, the degree of institutional ownership is generally rather high and does not contain too much variation. Including the interaction of CSR with the log market capitalization yields a clearer picture: for firms with an average $log(MarketCap)$, the direction of the effect of CSR on firm performance turns positive and is negatively moderated by the market capitalization. Again, this gives credence to the notion, that the insignificat/negative CSR effects documented in the focal specification are largely driven by investors in large-cap firms who are mostly institutional ones, and who tend to dislike long-term oriented investments in CSR.

Table 3.7: Regression results (incl. market capitalization and institutional ownership)

	Dependent Variable: $log(Tobins\_Q)$					
	(1)	(2)	(3)	(4)	(5)	(6)
CSR	-0.0203 (0.0125)	-0.0285 (0.0135)**	-0.0060 (0.0169)	0.2732 (0.1098)**	0.2597 (0.1262)**	0.3459 (0.1377)**
$InstitOwn * CSR$	-0.0003 (0.0006)	-0.0012 (0.0006)*	0.0002 (0.0008)			
$log(MarketCap) * CSR$				-0.0173 (0.0065)***	-0.0169 (0.0075)**	-0.0206 (0.0081)**
CSI	-0.0160 (0.0095)*	-0.0286 (0.0103)***	-0.0189 (0.0118)	-0.0155 (0.0089)*	-0.0266 (0.0097)***	-0.0119 (0.0110)
$CashETR * CSR$	0.0157 (0.0502)	0.0962 (0.0700)	0.0016 (0.0813)	0.0157 (0.0458)	0.0395 (0.0628)	-0.0338 (0.0717)
$CashETR * CSI$	0.1434 (0.0477)***	0.0458 (0.0622)	0.0985 (0.0714)	0.1567 (0.0445)***	0.1024 (0.0550)*	0.1457 (0.0614)**
$CashETR$	-0.0399 (0.0503)	0.0915 (0.0598)	0.0816 (0.0796)	-0.0603 (0.0458)	0.0952 (0.0549)*	0.0979 (0.0713)
ROA	0.0332 (0.0019)***	0.0297 (0.0018)***	0.0400 (0.0026)***	0.0365 (0.0017)***	0.0330 (0.0016)***	0.0413 (0.0022)***
$Leverage$	-0.0020 (0.0009)**	-0.0072 (0.0009)***	-0.0004 (0.0011)	-0.0033 (0.0007)***	-0.0072 (0.0007)***	-0.0011 (0.0010)
$log(Employees)$	-0.2554 (0.0226)***	-0.2185 (0.0233)***	-0.1836 (0.0295)***	-0.2711 (0.0184)***	-0.2419 (0.0191)***	-0.2210 (0.0238)***
N	2,856	2,452	1,581	3,436	2,986	1,877
Adj. R^2	0.905	0.875	0.922	0.900	0.870	0.918
Sample composition	Full	w/o Finance	B2C Focus	Full	w/o Finance	B2C Focus
Firm FEs	yes	yes	yes	yes	yes	yes
Year FEs	yes	yes	yes	yes	yes	yes

* p < .1, ** p < .05, *** p < .01

3.7 Conclusion

In this study, I assess the question whether refraining from aggressive tax avoidance can help a firm compensate for negative consequences of other types of socially irresponsible behavior, or in other words: Does paying taxes help to calm tempers?

Prior literature on socially (ir-)responsible behavior has mostly integrated tax disputes into a broader, less nuanced measure of CSI, hence making the detection of interactions between different forms of CSR and CSI impossible. By looking at firms' tax behavior separately, I examine the moderating effect of tax payments on the firm performance implications of other types of CSI. Borrowing from the idea that CSR has been shown to work as a tool of risk management in attenuating consequences of CSI, I would expect that a higher effective tax rate (i.e., refraining from aggressive tax avoidance behavior) should have a similar mitigating effect. I examine this question using a comprehensive panel data set with over 3,436 firm-year observations consisting of firms from the Fortune 500 list across 10 years. The data comprises firm financial information from the firms' annual reports as well as third-party CSR scores that is based on a variety of public information sources. Consistent across several model specifications, I find that (a) involvement in CSI negatively affects firm performance as measured by Tobin's Q, (b) a higher effective tax rate can dampen the negative effect of CSI, and (c) involvement in CSR can also adversely affect firm performance, yet mostly for large-cap firms with a high share of institutional (i.e., non-retail) investors. I believe that these results provide important insights for better understanding the role of tax payments in conjunction with the increasingly relevant field of CSR. The research contributes to existing literature in that it is the first to examine the interaction between tax payments and CSI incidents in terms of their joint impact on firm performance. I discuss implications and limitations of the research in the following sections.

3.7.1 Implications

Tax payments can mitigate the negative consequences of CSI. At the heart of this research, I study the moderating role of tax payments, measured by the cash ETR, in the relationship between other types of corporate misbehavior and firm performance. In line with the idea that tax payments can serve as a means of risk management, I show that a higher tax rate can weaken the negative firm performance implications of involvements in CSI. This result underpins the importance of tax payments for a firm and shows that by not trying to squeeze the tax burden down to the last dollar, even if this is within legal limits, firms can show good citizenship.

Involvement in CSI harms firm performance. My research findings with respect to CSI join a number of previous studies that document a negative effect of socially irresponsible activities as measured by third-party ESG ratings on firm performance measured by the market-based metric Tobin's Q. This is as expected, but again highlights the importance for firms to distance from behavior that is incompatible with the societal values of their customers.

Involvement in CSR may reduce firm performance for large-cap firms. Contrary to what the majority of previous research finds, my study provides no evidence that CSR has a generally positive impact for businesses. What is more, it appears to be the case that for big corporations with large market capitalizations and large shares of non-retail investors with rather short investment horizons, it can be even harmful to the financial performance to engage in CSR. Does this mean that companies should distance from making socially responsible investments whose ROI, if at all, will only be realized in the longer term? Looking at the purely monetary level, this may be true for large-cap corporations. However, the fact that companies nevertheless attach such great importance to CSR suggests that financial returns seem to be at least not the only metric, based on which investment decisions in CSR are made. Philanthropic motives and the pursuit of social goals that exceed the investment horizon of institutional owners might also play a role. For future research, it can be noted that the boundary conditions for the effectiveness of CSR as well as the exact motives for CSR engagement still have not yet been fully explored and deserve further attention.

Research on corporate (mis-)deeds should decompose CSR and CSI into their constituents. Considering the multi-faceted nature of the different dimensions of CSR or CSI activity (as can be seen in Table 3.5), it is easy to find examples of subcategories of CSR and CSI, respectively, that are only marginally related to each other. For instance, do savings in carbon emissions have much in common with minority representation in management? Presumably we can agree that these are two very different things. In the field of CSI, reports of workplace discrimination are also difficult to equate with corporate tax avoidance. Yet most research on CSP does just that by lumping together all the different dimensions of CSR and CSI. Using the example of corporate tax behavior, my research demonstrates that the separate consideration of different subcategories of CSR or CSI can be beneficial if the firm performance effects of different types of (un-)social behavior are not uniform and/or if they interact. Disentangling different forms of CSR and CSI, respectively, hence appears to be a promising avenue for future research, as it allows to identify potentially heterogeneous effects of different forms of social (mis-)deeds as well as their interactions.

3.7.2 Limitations

As with most research, this study is also not free of limitations. First and foremost is the temporal aggregation of MSCI ESG Ratings data described earlier in this study. Even though this is the *de facto* standard in CSR literature, having only annual measures of ESG strengths and weaknesses available that summarize all incidents that happened over the preceding twelve months makes it impossible to identify a clear temporal sequence of events. I try to address this issue by considering models with one-year lagged CSR performance in my robustness checks, yet future research might want to collect more disaggregated CSR data. Second, while I observe a relatively long period of time, my universe of firms is smaller than in many of the existing studies in the field. While this is a conscious choice to (a) focus on large US corporations and (b) to align the sample with the one used in Chapter 2 of this dissertation, this comes at the cost of a limited comparability with previous research. However, I think that by empirically examining the moderating effects of market capitalization and the share of institutional owners in my post-hoc analyses, I can reasonably explain the differences between the presented study and existing research. In spite of these limitations, my research can contribute to a better understanding of the joint impact of CSR, CSI, and tax payments on firm performance and my implications can guide decision makers to take informed actions in the interest of both their shareholders *and* society as a whole.

4

Exploring the Discourse of Corporate Taxes: A BERTopic Analysis of Tax-Related Firm Media Coverage

David Gremminger

Statement of contribution

This chapter constitutes a slightly modified version of the working paper "Exploring the Discourse of Corporate Taxes: A BERTopic Analysis of Tax-Related Firm Media Coverage". I, David Gremminger, am the sole author of this chapter. I confirm sole responsibility for the design of the study, for data preparation, for the analysis and interpretation of the results, as well as for manuscript preparation.

Acknowledgements: The author gratefully acknowledges Jonathan Fuhr for his helpful and constructive comments and feedback on an earlier version of the manuscript. Further, the author acknowledges support by the state of Baden-Württemberg through bwHPC.

Abstract

Newspapers assume an important role in the dissemination of information and in reducing asymmetries between institutions and the public. Media coverage is particularly important in the context of corporate activities, because the inner processes of a firm are often opaque to stakeholders and information asymmetries are therefore high. In this study, I focus on corporate tax behavior – an issue that is of utmost societal relevance, and in the context of which the media have revealed several incidents of corporate misbehavior in the recent past. Using BERTopic, a novel topic modeling algorithm, this study investigates which topics newspapers report when they mention companies in connection with taxes, and how prominent the issue of corporate tax avoidance is in the press, relative to other tax-related news. In examining this question, I demonstrate the potential of state-of-the-art topic modeling techniques for research in management and related disciplines, where these novel machine learning-based developments from computational linguistics seem to be neglected so far when it comes to analyzing firm news coverage.

4.1 Introduction

Newspapers and the media in general play an important role in society. They act as information intermediaries between institutions and their stakeholders by accumulating, consolidating, and evaluating information, thereby reducing information asymmetries (Deephouse, 2000). Media coverage is particularly significant when it comes to the activities of companies, since processes within a company are typically rather opaque to stakeholders, so information asymmetries are especially high (Graf-Vlachy et al., 2020). The importance of firm media coverage becomes particularly clear when it comes to corporate misconduct (Stäbler and Fischer, 2020), and several examples from the recent past show that oftentimes, this misconduct only becomes known to a broad public through investigative journalism (see for example reports about bad working conditions at *Amazon.com* logistics centers (Leonhardt, 2021), or the revelation of a large data privacy scandal at *Facebook* in 2018 (Cadwalladr, 2018)). By acting as "watchdogs" (Hachten, 1963), the media monitor areas of the society that would otherwise remain unseen.

One type of corporate activity pertains to the issue of taxes. Since taxes are an important source of revenue for the government and thus critical to financing public sector spending, societies expect profitable companies to pay their "fair share" (Schoen, 2014). Repeatedly in recent years, incidents have been uncovered, mainly by journalists, in which large corporations have failed to live up to this expectation (e.g., Bergin, 2012; ICIJ, 2014, 2017). In view of these developments, the general question arises as to what topics newspapers cover when they mention companies in the context of taxes, and how relevant the issue of corporate tax avoidance is in the press compared to other tax-related issues. The first contribution of this article is to shed light on this question, and to identify prevalent topics over time and across news outlets. To this end, I apply *BERTopic* (Grootendorst, 2022), a state-of-the-art neural topic modeling technique. The basis for the analysis is a collection of 34,645 newspaper articles from four major US news outlets that all mention the term "tax" jointly with firm names from the *Fortune 500* list of the largest US firms in terms of revenue.

In addition to investigating the question of which topics the media talk about when mentioning firms in a tax context, this study makes another important contribution, which is more methodological in nature. As I show in my literature review in Section 4.2, research in management and related fields often uses data from news articles to measure concepts such as media attention. Often, however, the literature to date seems to only scratch the surface of what is actually in the news article data. In most cases, researchers summarize the textual data using crude count-based metrics, often neglecting the actual content of the media coverage (e.g., Bednar, Love, and Kraatz, 2015; Chen et al., 2023; Jeon, McCurdy, and Zhao, 2022). In those studies that do look at the content of media coverage, the scope of analysis is usually limited to what can be handled with human labeling (e.g., Dixon-Fowler, Ellstrand, and Johnson, 2013; Rindova, Petkova, and Kotha, 2007). With my analyses, I showcase that modern topic modeling approaches such as BERTopic are capable of reliably identifying well-defined topic clusters in a collection of textual data that is prohibitively large for manual review. Besides showing which exemplary questions can be addressed with the method in Section 4.6, I outline some further potential use cases of the topic modeling technique along the research pipeline in Section 4.7.

The remainder of this study is structured as follows: I start with a review of literature about firm media coverage, focusing on papers that analyze the content of newspaper articles. After that, I outline some broad empirical predictions of what patterns I expect to find in the newspaper articles, and I theoretically motivate why I expect to find heterogeneous topic distributions across time and across news outlets. Next, I briefly introduce the news articles data set that the reader of this dissertation is already familiar with from Chapter 2, before I explain the topic modeling algorithm BERTopic in detail. In Section 4.6, I then present the results of my analyses by looking at five exemplary focal topics. To conclude, I discuss the insights of my study both from a substantive and a methodological perspective, and I close with potential limitations.

4.2 Literature

Over the past decades, previous literature has examined the role of the mass media in great detail and it has developed theories on the responsibilities of the media and about antecedents and consequences of media coverage. Something that has only become possible in recent years through the development of modern natural language processing (NLP) methods is an empirical evaluation of the actual content of media coverage at scale. In this section, I argue that these modern machine learning-based NLP methods have so far found little application in business-related scientific publications when it comes to analyzing firm news media coverage. To this end, I first outline the role of the media in the relationship between institutions and the broader public. After that, I present a series of empirical studies that rely on firm-related news media coverage as a data source. I show that few studies perform in-depth analyses of the content of news articles, which makes a case for applying the existing topic modeling techniques from computational linguistics to questions from the business and management disciplines.

In most Western democracies, the press has the right and the duty to report freely and critically on activities of institutions such as the government (Hachten, 1963). It is the responsibility of the free press to function as a "watchdog" and to keep a close eye on aspects of society that may otherwise remain hidden from the eyes of the broader public (e.g., Dyck and Zingales, 2002; Hachten, 1963). Kovach and Rosenstiel (2021, p. 202), for instance, see it as journalists' obligation and as one of the most important functions of the press to watch "over the powerful few in society to guard, on behalf of the many, against tyranny". Many misdeeds of companies who belong to these "powerful few" in society, to put it in the words of Kovach and Rosenstiel (2021), would have remained unnoticed if not for the press (Stäbler and Fischer, 2020). Prior research has identified media coverage as the primary factor that accelerates the transformation of negative corporate events into an actual crisis (e.g., Kölbel, Busch, and Jancso, 2017; Liu and Shankar, 2015). Consequently, the media play a crucial role as intermediaries between institutions and the public by shaping public knowledge and perceptions about corporate activities (e.g., Dyck, Volchkova, and Zingales, 2008; Van Heerde, Gijsbrechts, and Pauwels, 2015) and by reducing information asymmetries through the generation of new and dissemination of existing information (e.g., Bushee et al., 2010; Deephouse, 2000).

Scholars in business-related disciplines such as management, finance, accounting, or marketing have frequently relied on news media coverage of corporate activities to proxy for public attention towards selected issues and to study questions relevant to their respective domain (Graf-Vlachy et al., 2020). The scope and level of detail to which authors use media coverage varies widely, ranging from crude summary statistics to in-depth analyses of the content of newspaper articles. Carroll and Deephouse (2014) characterize attributes of corporate media coverage in terms of the four dimensions *volume*, *tone*, *timing*, and *topic*.

These dimensions have received varying degrees of attention in the literature, so far. *Volume* – typically measured by the (log of the) number of articles (e.g., Bednar, Love, and Kraatz, 2015; Chen et al., 2023; Jeon, McCurdy, and Zhao, 2022) or some measure of word frequency (Bushee et al., 2010) – is the most frequently used attribute of media coverage (Graf-Vlachy et al., 2020). Volume can be determined without much computational effort and it is therefore easily scalable to large collections of media coverage data. *Tone* refers to the evaluative aspect of a news article, i.e., whether the news coverage is favorable or unfavorable towards the subject of the report (Graf-Vlachy et al., 2020). Measures of the tone of media coverage are either based on subjective human evaluation (e.g., Chatterjee and Hambrick, 2011; Van Heerde, Gijsbrechts, and Pauwels, 2015), or on computer-assisted methods (e.g., Chen, Schuchard, and Stomberg, 2019; Kang and Kim, 2017). *Timing* of media coverage is an attribute that is usually implicitly accounted for in most studies by analyzing panel or time-series data of media coverage (e.g., Bednar, Love, and Kraatz, 2015; Wang and Chaudhry, 2018) or, for the purpose of event studies, by identifying first mentions of an event in the press (e.g., Hanlon and Slemrod, 2009). The fourth dimension of media coverage attributes is the *topic*, i.e., the content, of the news, and it is the attribute that has received the least attention in business literature thus far (Graf-Vlachy et al., 2020). Presumably, this is because traditionally the qualitative identification of the content of media coverage is very resource intensive and, if this step is done manually by human raters, has very limited scalability. Through the rapid advancements in the development of modern NLP methods in recent years, however, an automated empirical evaluation of the content of text documents at scale has become feasible (e.g., Blei, Ng, and Jordan, 2003; Grootendorst, 2022). With respect to firm-related news media coverage, publications in leading academic journals of business and management research do not yet reflect these new algorithmic developments, as Table 4.1 shows. To select the articles presented in Table 4.1, I build on the literature review of Graf-Vlachy et al. (2020). Between 1997 and 2017, Graf-Vlachy et al. (2020) identified ten articles in top-tier management, finance, accounting, or marketing journals, that consider the *topic* of firm news media coverage, with the oldest article being published in 2007. Using the same filtering criteria as Graf-Vlachy et al. (2020)[1], I expand this list to include publications through 2023, which yields the total of 14 relevant articles that I present in Table 4.1. For all 14 articles, I gather details about the context of the media coverage analyzed and about how the authors classify and operationalize the content of firm media coverage. I distinguish between four types of content operationalizations: human judgement, keyword filtering, predefined content tags, and automated analyses. Human judgement refers to methods that involve human raters reading articles and manually classifying or labelling them according to specific criteria. Examples are the studies by Chatterjee and Hambrick (2011), who let two raters identify whether or not an article contains evaluative comments about the CEO of a firm, or by Rindova, Petkova, and Kotha (2007), where raters extracted and categorized different types of activities of new ven-

[1]For the details of the literature review process, including the list of journals considered, see Appendix C.1

Table 4.1: Literature analyzing topic of firm-related news media coverage

			Type of content analysis			
Study	**Context of media coverage**	**# of articles**	**Human judgement**	**Keyword filtering**	**Predefined content tags**	**Automated analysis**
Chatterjee and Hambrick (2011)	*CEO reputation*	*Not reported*	✓			
Dixon-Fowler, Ellstrand, and Johnson (2013)	*Female CEO appointments*	Coverage of 45 events	✓			
Rindova, Petkova, and Kotha (2007)	*Reputation accumulation of start-ups*	148	✓			
Durand and Vergne (2015)	*Media attacks in stigmatized industries*	~ 3,000	✓	✓		
Hope et al. (2021)	*Tunneling scandals*	37,944	✓	✓		
Ahern and Sosyura (2015)	*M&A rumours*	2,142		✓		
Beattie et al. (2021)	*Car safety recalls*	13,600		✓		
Col, Durnev, and Molchanov (2018)	*Political instability*	19,816		✓		
Kang and Kim (2017)	*CEO exposure*	104,129		✓		
Tetlock, Saar-Tsechansky, and Macskassy (2008)	*Financial news*	~ 350,000		✓		
Drake, Guest, and Twedt (2014)	*Earnings announcements*	111			✓	
Bushee et al. (2010)	*Earnings announcements*	600,478			✓	
Foerderer and Schuetz (2022)	*Data breaches*	*Not reported*			✓	
Tetlock (2011)	*Staleness of news*	*Not reported*			✓	✓
This study	*Tax-related media coverage*	34,645		✓		✓

tures. While methods that involve human judgement can potentially identify very nuanced and detailed information from texts, analyses are typically limited to a few hundred articles, since this procedure requires extensive human resources.[2] To be able to efficiently leverage content information from larger collections of news articles, many researchers rely on heuristics that involve filtering for keywords. These methods are based on the assumption that mentioning certain keywords indicates with sufficient reliability that a text is about a certain topic. The implementation of a keyword search is feasible even in very large data sets without significant computational costs, which is why keyword based content analysis methods are frequently used once the number of articles reaches the thousands.

In Table 4.1, the largest collection of articles analyzed with keyword-based methods is the one in the study by Tetlock, Saar-Tsechansky, and Macskassy (2008) with about 350,000 articles, but there is now virtually no limit as to the scalability of these methods to much larger data sets. Since the mere search for keywords in text documents is purely count based and does not take into account the semantic context in which a word is mentioned, these methods provide only rather crude measures for the topic of the news media coverage. A third category of operationalizations of topics in media coverage are predefined content tags, i.e., tags that a data provider assigns to news articles and which give a hint of what the article is about.[3] Since (a) this requires that such tags are available, (b) the data providers' process of generating these tags is not always transparent, and (c) using these predefined tags does not involve an actual analysis of the textual data on the part of the researcher, I do not further discuss these studies here.

Finally, there is the possibility of examining text data algorithmically for its topic attributes, i.e., in a fully automated way without the manual classification, the use of keyword filters, or the use of predefined topic tags. In contrast to human judgment methods, these automated procedures are much more scalable to very large data sets. At the same time, modern NLP methods provide the ability to capture the semantic meaning of a text much better than purely count-based keyword methods. In the context of firm-related news media coverage, only the study by Tetlock (2011) falls into this category in the broadest sense. Tetlock (2011) does not extract the actual topic from articles, but calculates pairwise similarities between a focal news

[2]The study by Hope et al. (2021), in which more than 30,000 articles from the Chinese media landscape are hand-labeled, poses an exception to this.

[3]Examples of data providers offering article tags are *Factiva* (used in Bushee et al. (2010)), *RavenPack* (used in Drake, Guest, and Twedt (2014)), *Dow Jones Newswire* (used in Tetlock (2011)), and the *Identity Theft Resource Center* (used in Foerderer and Schuetz (2022)).

article and the ten preceding news articles about the same company, respectively, to decide whether an article contains new information or whether it is just a follow-up story to a previous article. Modern NLP methods, which are capable of automatically detecting and extracting the semantic meaning of a text and which are state-of-the-art in computational linguistics, have not yet attracted a lot of attention in the literature on firm media coverage.

This study aims to bridge this gap by showing an application of BERTopic (Grootendorst, 2022), a state-of-the-art neural topic modeling technique, to firm-related news article data. More specifically, I perform an in-depth analysis of what topic the newspapers discuss when they talk about firms in a tax context. I show that, without the need for human labeling or for an informed selection of appropriate keywords, the method is capable of reliably identifying topics discussed in a large collection of 34,645 news articles, and to capture temporal patterns in topic prevalences. Besides yielding substantive insights regarding the content of tax-related firm media coverage, the results of this study also suggest that researchers in the field of business and management do not yet fully exploit the information content of textual news media data about firm activities. It appears that often, researchers only scratch the surface of what is actually in the data. I would like to propose that we should make more use of machine learning-based NLP tools such as BERTopic to realize the full potential of news media data.

4.3 Empirical Predictions

This study follows an empirics-first approach as described by Golder et al. (2022). The authors propose the empirics-first approach as a modern paradigm to knowledge generation, that reflects today's evolution toward a data-rich environment. At the heart of this approach is the explorative analysis of real-world data with the goal of generating new findings regarding a relevant topic, as opposed to the a priori more narrowly defined research pipeline of traditional theory-driven research. In that vein, my study aims to discover interesting and relevant phenomena within a unique data set, starting off with a rather generic research question, namely what topics newspapers talk about when they report about corporations in the context of taxes, and refining this question iteratively as I move along the research process.

Although I want to remain deliberately open about my main research question, and let the exploration not be constrained by narrow formal hypotheses, I attempt to sketch out some fairly broad theoretical expectations in this section about what I expect to find in my data. Also, I outline theoretical considerations motivating the investigation of different dimensions in the data, such as temporal differences in topic prevalence, or topic distribution across different news outlets. I present a schematic short summary of my empirical predictions in Table 4.2.

The selection and framing of topics covered in newspaper articles are to some degree subject to editorial decisions (e.g., Gentzkow and Shapiro, 2006; Stäbler and Fischer, 2020). These editorial decisions, may in turn be driven by, for example, the political orientation of the publishing house (Larcinese, Puglisi, and Snyder, 2011) or partnerships with advertisers (Gal-or, Geylani, and Yildirim, 2012). The line along which a newspaper chooses topics is also called the newspaper's *agenda* (Harcup and O'Neill, 2001) and my selection of US newspapers covers a broad range of the political spectrum from rather liberal outlets such as *The Washington Post* or *The New York Times* to *The New York Post*, which is rather right-oriented and embraces conservative positions (Ad Fontes Media, 2023). When it comes to taxation, it is a typical left-wing position to "tax the rich" whereas the political right rather calls for tax cuts. Also the type of the newspaper, and therefore the target audience, likely determines which topics an outlet covers, and how intensely it does so. I expect a business specialist newspaper such as the *Investor's Business Daily* to have a strong focus on investment-related news, like for example recent developments on the capital markets or in fiscal policy. A tabloid newspaper like *The New York Post*, on the other hand, probably reports about less technical topics and possibly does so in a more polarizing way. I expect this phenomenon to be reflected in my data as well in the form of heterogeneous topic prevalence across the different newspapers.

Next, I expect that topics that prevail in the newspapers are changing over time. While I expect some topics encompassing firm-initiated information (such as reports on new figures from the corporations' financial statements) to occur regularly and consistently over the entire period of observation (for instance, at the end of every fiscal quarter), I expect topics covering press-initiated information (such as revelations in the context of tax data leaks) to have a much less stable prevalence in the news media. In the investigated time period between 2009 and 2019, I want to highlight two themes for which I expect volatile attention patterns over time: First, the major tax data leaks that happened during the time of observation (i.e., *LuxLeaks* in 2014 and *Paradise Papers* in 2017), and second, the discussions about and enforcement of the *Tax Cuts and Jobs Act* in 2017 under the US presidency of Donald Trump. I expect that major events like these should dominate press coverage in the months around their occurrence.

Table 4.2: Empirical predictions along selected dimensions

Dimension	Expectation
News outlet	• Newspaper agendas differ along with political orientation, editorial line, relationships with advertisers, etc. • Focus of tax-related reporting differs between broadsheet, specialist business, and tabloid newspapers
Time	• Prevalence of topics is dynamic and big topics rise and fade over time • Major themes (e.g., tax data leaks or important changes in tax legislation) should dominate press coverage in the months around their occurrence

To conclude this section, I want to restate that this study follows an explorative approach. For this reason, the empirical predictions formulated throughout this chapter are not to be understood as formal and (in a statistical sense) testable hypotheses, but are rather meant to guide the reader through my considerations that led to the investigation of the respective dimensions. In the discussion of my analyses in Section 4.6, I revisit the empirical predictions made here and attempt to reconcile them with the results of the analyses.

4.4 Data

The data basis for this study is a text corpus consisting of about 35,000 English-language newspaper articles that were published between January 2009 and April 2019 in *The New York Times* (abbreviated as *NYT* in the remainder of this section), *The New York Post* (*NYP*), *The Washington Post* (*WP*), and *Investor's Business Daily* (*IBD*). Since the reader of this dissertation is already familiar with the data from Chapter 2, I only briefly reiterate the data collection process below and then move on to a more detailed description of the data.

I collect data from the news database *LexisNexis* performing a multi-step keyword search. The goal of the data collection is to identify all newspaper articles in the aforementioned news outlets that mention the term "tax" together with at least one reference to a firm from the 2018 Fortune 500 list of the largest US-based companies by revenue. Since my original list of Fortune 500 companies contains only one variant of each firm name, while there are potentially many different alternatives to refer to the same company, I am proceeding in several steps to make sure I identify all relevant articles. In a first step, I collect a set of over 10,000 firm-unspecific business news articles. On this collection of text documents, I run a named-entity recognition

(NER) algorithm to automatically detect different types of entities, such as organizations or firms, in unstructured text (Thomas and Sangeetha, 2019). I match the resulting NER-based list of firm names with the original Fortune 500 name list. I do this semi-automatically by first computing pairwise string distances between all original firm names and all organization names identified with NER, and then assigning the most orthographically similar strings by hand. Importantly, this step helps in finding alternate (but orthographically similar) spellings of a firm name (e.g., *Walmart* and *Wal-Mart*), but it fails to uncover abbreviations or entirely different names for the same company (e.g., *GM* for *General Motors* or *Alphabet* and *Google*). To also capture these alternatives, I perform a structured manual web search in which I scan the introductions of the Wikipedia articles of each firm for alternative names. A typical Wikipedia article about an organization hints to potential alternative names or abbreviations in the first sentence.

I finally use all alternative firm names compiled in the previous steps to query all articles between January 2009 and April 2019 from LexisNexis with a keyword search filtering for articles mentioning a firm and the term "tax". After dropping some articles and firms (for the detailed description of this step, please refer to Section 2.4.2), my data collection yields a corpus of 34,645 relevant news articles that refer to at least one firm. Before analyzing the data, I remove the company mentions so that the identified topics are not driven by company names but actually reflect the substantive content of the newspaper article. I present summary statistics of the number of articles across outlets as well as the article lengths as measured by the number of words per article in Table 4.3. With 16,533 articles (48 percent of all articles in the sample), the *NYT* account for the largest share of articles in my sample, followed by the *WP* with 10,052 articles (29 percent), and *IBD* and the *NYP* with 5,647 (16 percent) and 2,413 (7 percent), respectively. The average article in the sample is 1,171 words long. For reference, this is roughly equivalent to about one-third to one-half page in a broadsheet newspaper. I find the shortest articles in the sample to be three-liners that contain not much more than a headline and sometimes announce a larger article to come. The shortest article in the sample consists of only 30 words and appeared in the *WP*. The longest articles were published in the *NYT* with up to 30,467 words. A look at the raw data reveals that these few exceptionally long articles are for example special issues of *The NYT Magazine* featuring one long story on a selected topic[4] or

[4]See for example the August 2018 issue of *The New York Times Magazine* on climate change: https://www.nytimes.com/interactive/2018/08/01/magazine/climate-change-losing-earth.html (last access: April 11, 2023)

Table 4.3: Descriptive statistics of article lengths (number of words per article)

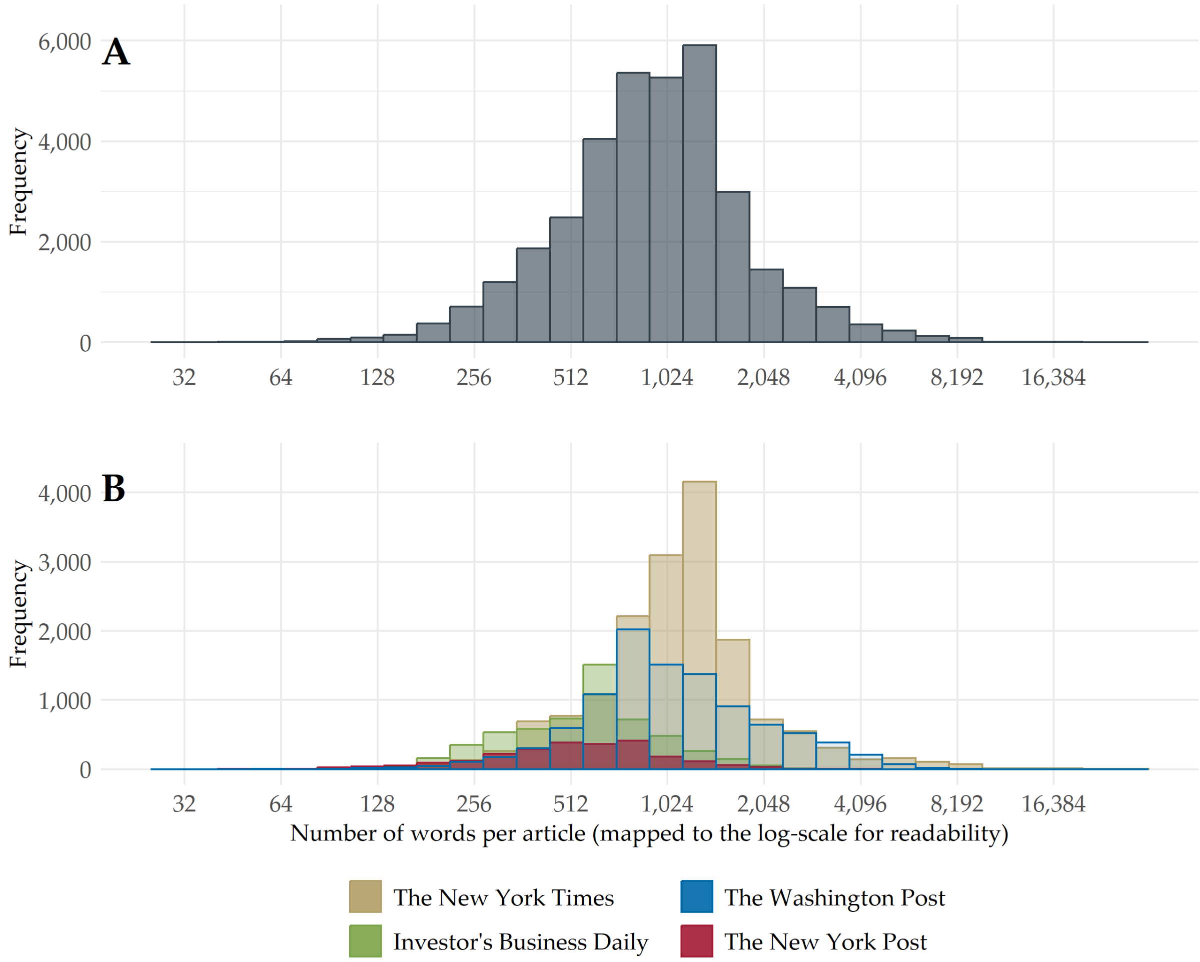
Sample	**N**	**Min.**	$Q_{0.25}$	**Median**	**Mean**	$Q_{0.75}$	**Max.**	**SD**
All outlets combined	34,645	30	631	940	1,170.88	1,358	30,467	1,098.46
The New York Times	16,533	34	815	1,135	1,353.00	1,437	30,467	1,309.10
The Washington Post	10,052	30	724	990	1,295.27	1,533	16,681	963.08
Investor's Business Daily	5,647	45	389	618	645.28	770	4,157	366.06
The New York Post	2,413	49	358	550	635.90	805	5,282	424.38

transcriptions of political debates occasionally published in the web version of the respective newspapers.[5]

While these documents are clearly outliers in the sense that they are not representative of the typical length of other news stories, I still keep them in the sample since they contain information about what issues are shaping public discourse. Unsurprisingly, articles have very different lengths across outlets, with the two broadsheet newspapers (the *WP* and the *NYT*) having by far the longest articles, on average, and the tabloid newspaper the *NYP* publishing substantially shorter articles with an average length of only 635 words. It is important to note that the higher average lengths in the *WP* and the *NYT* are not only driven by extremely long outliers, but also that the bulk of articles are significantly longer, as is illustrated in Panel B of Figure 4.1. Figure 4.1 visually shows the distribution of article lengths across all articles jointly in Panel A, and broken down by news outlet in Panel B. To achieve a better readability of the histograms, I log transformed the x-axis. I report the histograms without the log transformation in Appendix C.2.

The final dimension I consider in this chapter is the evolution of article volume over time. To this end, I aggregate all relevant news articles to a monthly level for every news outlet. The stacked area chart in Figure 4.2 shows the development of the total article volume over time (indicated by the the shape of the colored area at the upper edge) as well as the shares that the different news outlets have at every point in time (depicted by the colors of the areas). Once again, it can be seen that the *NYT* accounts for the largest share and that this share increases significantly near the end of the observation period. It is notable that the total article volume sharply increases towards the end of 2016. I identify two reasons for this increase. First and

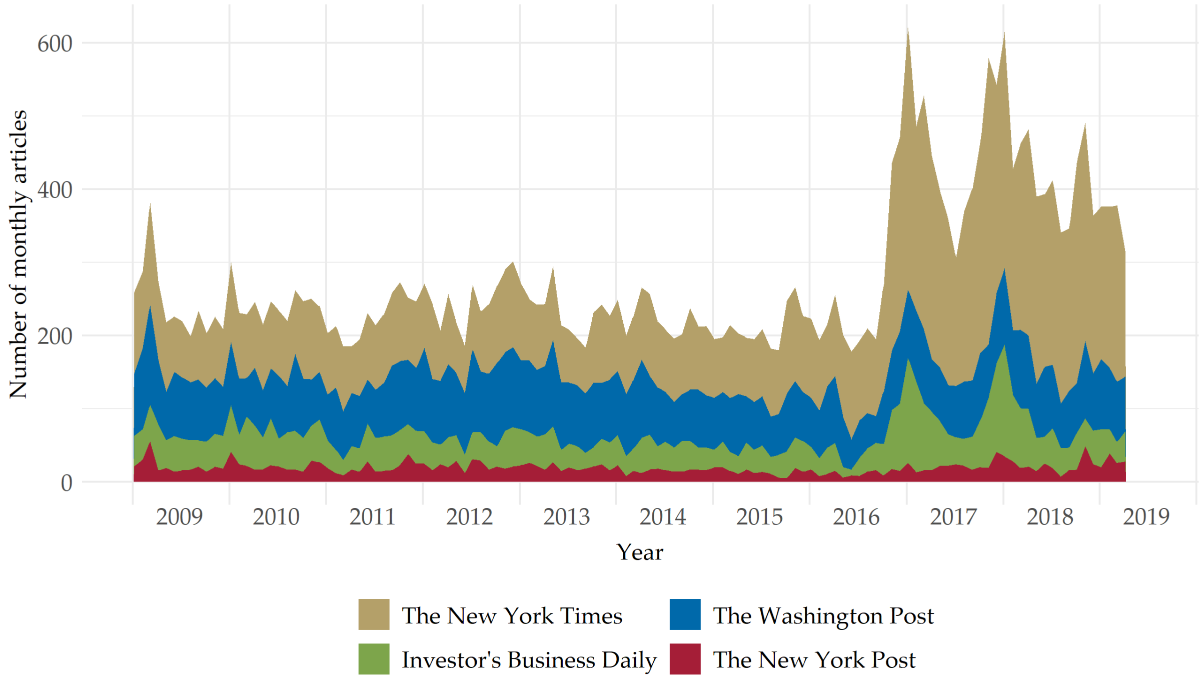
[5]See for example the transcribed version of a Republican presidential debate prior to the 2016 US presidential elections here: https://www.nytimes.com/2016/02/26/us/politics/transcript-of-the-republican-presidential-debate-in-houston.html (last access: April 11, 2023)



Panel A shows the data in aggregated form, Panel B shows the histograms broken down by news outlet.

Figure 4.1: Histograms of article lengths (number of words per article; log-scale)

foremost, the *NYT* almost doubles its article volume from late 2016 onwards, showing much larger portion of exclusive web content such as *NYT* blog articles. This is most likely driven either by a technical change at the data provider *LexisNexis* or by a change in the publication strategy at the *NYT*. For the purpose of this study, I do not consider this observation problematic since web sources may be equally important in shaping public perceptions about firm behavior as are print articles. Second, the data path of *IBD* shows two substantial spikes towards the end of 2016 and the end of 2017. It is subject to my later analyses to understand this anomaly and to identify the topics discussed in these time periods.



Articles in individual outlets are stacked to show both evolution of total article volume and distribution across different news outlets.

Figure 4.2: Number of monthly articles over time

4.5 Method

To examine the text corpus of news articles, I employ *BERTopic*, a novel topic modeling technique proposed by Grootendorst (2022). Grootendorst (2022) suggests a flexible framework that (1) leverages the capacity of pre-trained language models to embed the semantic meaning of text documents into dense numerical vector representations, (2) reduces the dimensionality of the document embeddings, (3) creates clusters of semantically similar documents, and (4) creates topic representations using a class-based term frequency-inverse document frequency (c-TF-IDF) procedure. Figure 4.3 schematically presents the pipeline of the method. This section elaborates on the four aforementioned steps of the BERTopic pipeline. Whenever possible, I contrast this state-of-the-art neural method with conventional bag-of-word approaches to topic modeling. Bag-of-words approaches are characterized by considering individual words as part of a "bag", in the sense that the syntax and thus the context of the words are disregarded. Bag-of-word methods are therefore solely based on word frequencies in documents and the most popular example from this family of methods is the Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan, 2003).

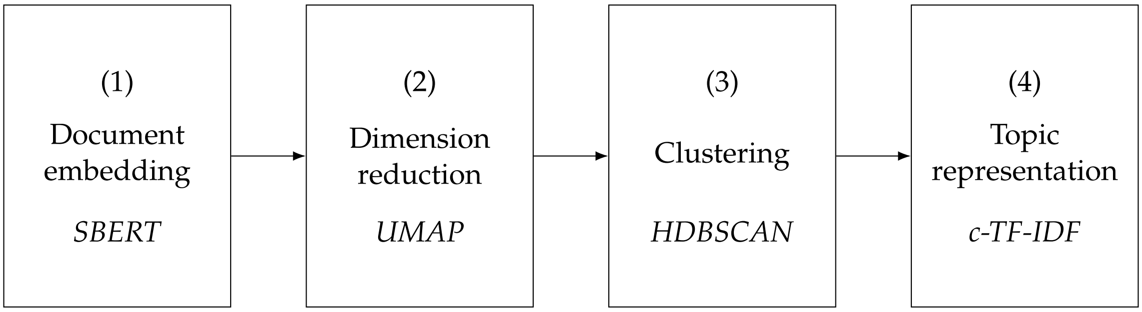


Figure 4.3: BERTopic pipeline (algorithm applied in each step printed in italics)

Step 1: Creating contextual document embeddings. BERTopic builds on the powerful language models that NLP research has produced in recent years. In its default configuration, BERTopic uses Sentence-BERT (SBERT) (Reimers and Gurevych, 2019), a variation of the BERT network (Devlin et al., 2019), to create vector representations of the semantic meaning of a document. BERT stands for "Bidirectional Encoder Representations from Transformers" and is bidirectional in the sense that it produces language representations that account for context to both the right and the left side of the focal token[6] (Devlin et al., 2019), as opposed to unidirectional left-to-right architectures that only consider context to the left of the focal token. The ability to view language in context fundamentally differentiates BERT from bag-of-word approaches in that it allows to capture not only the frequency of individual words across documents, but to also produce language representations that are contingent on the surrounding words (Grootendorst, 2022). To illustrate, consider the following two exemplary sentences: (a) *"I own a firm."* and (b) *"I have firm beliefs."*. Although lexically identical, the word "firm" has a very different meaning in the two sentences. Bag-of-word approaches would not be able to capture these different meanings in a numerical representation, but would use, for example, the information that the word "firm" occurs once in both sentences, each of which consists of a total of four words. Contextual embedding techniques, such as BERT, in contrast, would generate different vector representations (so-called *embeddings*) for "firm" depending on the surrounding words. As a result, the embeddings of a token in the high-dimensional vector space are closer together when the token conveys the same meaning, as opposed to when the same token occurs with a different meaning. While the standard BERT network (Devlin et al., 2019) is fine-tuned to embed the semantic meaning of words, SBERT (Reimers and Gurevych, 2019) is optimized to embed

[6]In the context of NLP, a token is a meaningful sub-unit of text, such as a paragraph, a sentence, a word, sub-word or punctuation mark.

the semantic properties of sequences of words, i.e., sentences, paragraphs, documents. The modular design of BERTopic allows to use any other embedding technique instead of SBERT, however, for the purpose of this study, SBERT appears to be suitable. Specifically, I rely on the pretrained "all-MiniLM-L6-v2" transformer model (Reimers, 2022) to create the document embeddings since this yields good clustering results in terms of semantic interpretability while showing reasonable computation times. "all-MiniLM-L6-v2" has a maximum sequence length of 256, meaning that longer documents are being truncated to the first 256 tokens. This makes the implicit assumption that the first 256 words are representative for the complete document, which is not unreasonable to assume, since the main theme of a newspaper article is typically stated in the first paragraph. I also run my analyses using other transformer models such as "all-distilroberta-v1" with a maximum sequence length of 512 words, but this has no noticeable influence on the structure of the topics identified.

Step 2: Reducing embedding dimensionality. For the clustering that follows in step 2, the high dimensionality of the document embeddings (384 dimensions in the case of "all-MiniLM-L6-v2") poses a potential challenge, since distances between data points in high-dimensional space converge (Grootendorst, 2022) – a property of high-dimensional data that is often referred to as *the curse of dimensionality* (Bellman, 1961). To overcome this issue, Grootendorst (2022) suggests to reduce dimensionality using the UMAP algorithm (short for <u>U</u>niform <u>M</u>anifold <u>A</u>pproximation and <u>P</u>rojection) (McInnes, Healy, and Melville, 2020). UMAP is a flexible technique that can handle all embedding dimensions and is superior to comparable algorithms, such as t-SNE (van der Maaten and Hinton, 2008), both in its ability to preserve the local and global structure of the embeddings and in terms of its computational efficiency (McInnes, Healy, and Melville, 2020). Among a variety of models trained with different combinations of parameter values, a specification with *n_components = 5* and *n_neighbors = 100* showed the best coherence and interpretability of the generated topics. The *n_components* parameter determines the target embedding dimension (McInnes, Healy, and Melville, 2020). With the *n_neighbors* parameter, I limit the size of the local neighborhood considered by UMAP and thus it represents the trade-off between a focus on the fine grained local structure (which may introduce more noise and artifacts) versus the larger scale global structure, i.e., the more general features, of the original embeddings (McInnes, Healy, and Melville, 2020).

Step 3: Clustering documents. Using the embeddings with a reduced dimensionality of 5 (for robustness checks, I also use 2- or 10-dimensional embeddings), I cluster the data points by applying the HDBSCAN algorithm (McInnes, Healy, and Astels, 2017) as suggested by Grootendorst (2022). HDBSCAN is a hierarchical clustering algorithm that is able to identify clusters of varying shapes and sizes in relatively high-dimensional settings (McInnes, Healy, and Astels, 2016, 2017). Being a soft clustering technique, HDBSCAN allows noise in the data to be treated as outliers, i.e., data points are not necessarily forced into a cluster if the algorithm considers them too dissimilar (McInnes, Healy, and Astels, 2016). This distinguishes HDBSCAN from other widely used clustering algorithms, such as k-means clustering, which per construction assign every data point to exactly one cluster. Grootendorst (2022) argues that this yields better topic representations, as no unrelated documents are included. After running several alternative specifications, I define a minimum cluster size of 100 in my focal model to receive document clusters of substantial size and importance. I set the *min_samples* parameter to 100 as well. This parameter determines how "conservative" the algorithm is in declaring a data point as noise (McInnes, Healy, and Astels, 2016). With the chosen parameter settings, HDBSCAN models relatively dense clusters with a moderate amount of outliers, capturing well-defined clusters with good interpretability.

Step 4: Creating topic representations. Once all documents are defined in step 3 as either members of a cluster or noise (i.e., outliers), BERTopic creates topic representations. While the clustering happens based on non-interpretable numeric document representations, the topic representations in step 4 are intended to provide human-comprehensible insight into which words have particularly informative topic membership. To achieve this, Grootendorst (2022) proposes class-based TF-IDF (c-TF-IDF), which is a variant of the conventional TF-IDF procedure (Salton and Buckley, 1988). TF-IDF is a weighting scheme for term frequencies within documents, that aims to assess the importance of a term to a document within a collection of documents (Rajaraman and Ullman, 2011). In other words, a term with a higher TF-IDF score is more characteristic to a document and has more discriminatory power regarding other documents than a term with a lower TF-IDF. The standard TF-IDF definition is:

$$TF - IDF_{t,d} = tf_{t,d} \times log(\frac{N}{df_t}) \tag{4.1}$$

where $tf_{t,d}$ is the frequency of term t in document d, N the total number of documents, and df_t the number of documents that contain term t (Salton and Buckley, 1988). As a consequence, TF-IDF scores highest if a term occurs often in the focal document ($tf_{t,d}$ high), but in relatively few documents overall (df_t small relative to N). Grootendorst (2022) develops c-TF-IDF by adapting TF-IDF to capture the importance of a term (or a bigram) to a *class* (i.e., a topic). To do so, he proposes the following metric:

$$c - TF - IDF_{t,c} = \sqrt{tf_{t,c}} \times log(1 + \frac{A}{tf_t}) \tag{4.2}$$

where class c represents the concatenation of all documents that belong to this class, consequently $tf_{t,c}$ is the frequency of term t in this class, A is the average number of words per class, and tf_t is the frequency of term t across all classes.[7] This operation yields a c-TF-IDF score that represents the importance of a term to a topic. Based on these topic representations consisting of the most important words and bigrams, I assign labels, i.e., names, to the top topics based on my subjective assessment of the underlying theme. As an extension to the global topic model (i.e., the model considering all 34,645 articles jointly), I also look at topic representations over time. To do so, I use the topics generated by the global model and rerun step 4 for subsets of the articles. I create these subsets by splitting the observation period into 50 bins of equal length (this yields time windows each about 2.5 months long). I then recalculate topic representations for every bin, which allows me to identify potential differences in the way a topic is discussed over time.

4.6 Results and Discussion

In the following, I present the results of my topic models by revisiting the questions and predictions outlined in Section 4.3. The structure of this section is as follows: I first present the results of the global topic model, i.e., the topic model across all 34,645 news articles, irrespective of the news outlet and the time in which they appeared. After that, I show the distributions of topics per class, where a class represents the newspaper that an article comes from. Next, I present my results with regard to the topic prevalence over time. For the sake of illustration, in each of the aforementioned steps I pick out the same five topics (*"Capital markets"*, *"US elections"*, *"Tax cuts"*, *"Banking crisis"*, and *"Corporate tax avoidance"*) that show to have particularly interesting

[7]The default c-TF-IDF specification reads $tf_{t,c} \times log(1 + \frac{A}{tf_t})$, but taking the square root of the term frequency in class ($tf_{t,c}$) further reduces the likelihood of very frequent (and thus not distinctive) words to appear in the topic representations. See: https://maartengr.github.io/BERTopic/getting_started/ctfidf/ctfidf.html#reduce_frequent_words (last access: April 11, 2023)

characteristics and examine and discuss them in detail as examples.[8] The results presented in these subsections are based on my focal model specification, which I selected from a rich set of different model runs with different parameter settings to obtain robust, coherent, and interpretable topic representations. I conclude this section by showing condensed results for two alternative model specifications to highlight the robustness of this approach.

4.6.1 Global topic model

The focal model specification yields 51 topic clusters with the largest cluster (*"Capital markets"*) containing 1,256 articles and the smallest cluster (*"Schooling and education"*) 103 articles (note that I set the *min_cluster_size* parameter to 100, defining this value as the lower bound). It is important to emphasize that this does not imply that 1,256 articles *only* deal with the capital markets. Topics can be potentially diverse within a document, topics can overlap, and do not need to be mutually exclusive. BERTopic therefore generates a probability for each article-topic combination, indicating how likely it is that an article belongs to a certain topic, or in other words, what portion of the article deals with that particular topic. The assignment of an article to a cluster then happens in a binary way, choosing the topic with the highest probability. Being a soft-clustering algorithm, HDBSCAN classifies an article as outlier if none of the topics has a sufficiently high probability to assign the article to a topic cluster. This is the case for approximately half of the articles (15,210) in my focal model specification. Table 4.4 shows the most frequently assigned topics along with a topic label which I assigned manually. Further, it shows the topic representation in terms of the top words or bigrams in the respective cluster, the number of articles belonging to this topic cluster (N) and the relative cluster size (not including outlier articles). For a complete list of all 51 identified topics, see Appendix C.3. I find a variety of different topics in the list ranging from (geo-)political issues (e.g., *"US elections"*, *"NYC local affairs"*, *"Trade with China"*), where taxes play a minor role, to financial news (e.g., *"Capital markets"*, *"Corporate tax avoidance"*, *"Tax cuts"*) where (corporate) taxes seem to be the focus. As indicated above, in the remaining section I exemplarily focus on the five themes *"Capital markets"*, *"US elections"*, *"Tax cuts"*, *"Banking crisis"*, and *"Corporate tax avoidance"*. For representative articles for each of the focal topics (i.e., the articles that have the highest proba-

[8]The topic names provided here are not a direct result of the topic model, but assigned by me based on my subjective interpretation of the respective topic representations.

Table 4.4: Most prevalent topics and their global representations

ID	Topic label	Global topic representation (Top 15 words or bigrams)	N	Share
1	Capital markets	stocks - stock - dow - percent - index - rose - market - earnings - fell - cents - points percent - dow jones - shares - investors - jones industrial	1,256	6.5%
2	Energy	energy - oil - climate - solar - gas - carbon - coal - climate change - wind - power - emissions - natural gas - natural - drilling - environmental	1,116	5.7%
3	Tax cuts	tax - taxes - cuts - obama - republicans - corporate - budget - senate - spending - income - house - congress - tax cuts - plan - rate	1,044	5.4%
4	US elections	republican - trump - clinton - campaign - party - governor - romney - applause - voters - senator - democratic - democrats - candidates - mr - rubio	1,002	5.2%
5	NYC local affairs	city - square - building - buildings - new - new york - york - metro - transit - seattle - headquarters - project - space - development - square feet	957	4.9%
6	Electromobility	electric - cars - car - vehicles - volt - ford - battery - model - vehicle - auto - toyota - musk - chrysler - automakers - hybrid	872	4.5%
7	Trade with China	china - tariffs - trade - chinese - united states - united - beijing - states - trump - steel - american - imports - tariff - trade war - goods	790	4.1%
8	Health insurance	health - insurance - care - coverage - insurers - health care - obamacare - premiums - health insurance - medicare - medicaid - care act - affordable care - plans - affordable	761	3.9%
9	Middle East policy	page - israel - callimachi - islamic - netanyahu - islamic state - minister - israeli - military - syria - egypt - iraq - afghanistan - pakistan - police	669	3.4%
10	Banking crisis	banks - bonuses - financial - bank - compensation - wall street - wall - executives - crisis - pay - firms - billion - street - bailout - regulators	644	3.3%
11	Medicine/drugs	drug - drugs - allergan - mylan - pharmaceutical - astrazeneca - valeant - shire - cancer - patients - inversions - generic - deal - pharmaceuticals - billion	533	2.7%
12	Corporate tax avoidance	ireland - luxembourg - european - tax - profits - taxes - irish - corporate - multinational - companies - european union - corporate tax - avoidance - countries - europe	480	2.5%
13	Telecommunication	mobile - cable - wireless - sprint - vodafone - subscribers - tv - charter - billion - analyst - malone - analysts - network - directv - customers	471	2.4%

Notes: Topic labels are manually assigned based on the topic representations. "N" is the number of articles in which the respective topic is dominant, "Share" refers to the relative frequency of the topic across all articles (not including outliers); i.e.: N/(# of articles - # of outliers).

bility to belong to a particular topic) see Appendix C.4. I show a visual representation of the focal topic model in the form of a two-dimensional UMAP graphic in Appendix C.5.

4.6.2 Topics per news outlet

As outlined in Section 4.3, different news outlets may have different emphases in their reporting. I therefore believe it is worthwile to look at the topic frequencies per news outlet. I present the relative frequencies of the focal topics in Figure 4.4. The y-axis shows the five focal topics, the x-axis shows the share of articles belonging to each topic, grouped by news outlet (the outliers are not included in the reported percentages). The most evident feature of Figure 4.4 is visible for the topic *"Capital markets"*, where the topic prevalence is most heterogeneous between outlets. Not surprisingly, articles about *"Capital markets"* are by far the most prevalent in *Investor's Business Daily*, a business specialist newspaper whose core agenda is to inform investors about developments at the capital markets. Among all non-outlier articles published in *IBD*, about 20 percent belong to the topic *"Capital markets"* – four to ten times the frequency of the same topic in other news outlets. Political issues, such as the *"US elections"*, in turn, are strongly underrepresented in *IBD* as opposed to the other news outlets considered, especially compared to the broadsheet newspapers *NYT* and *WP*. The complex issue of *"Corporate tax avoidance"* is most prevalent in the left-liberal oriented *NYT* and least covered in the rather conservative tabloid newspaper *NYP*. All in all, I find my broad a priori expectations about the distribution of the topics across news outlets supported through the exemplary analyses of my five focal topics.

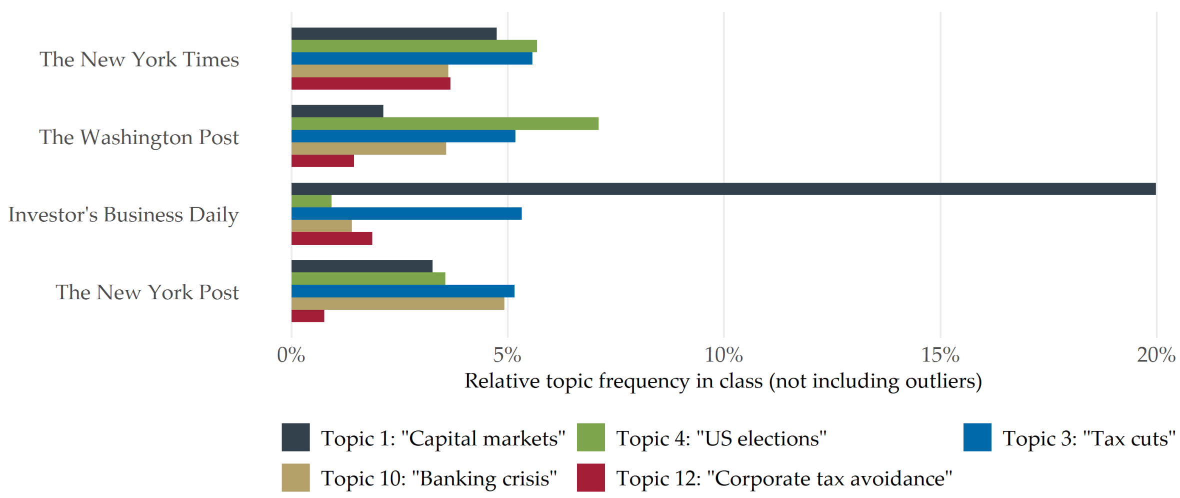


Figure 4.4: Topics per class

4.6.3 Topics over time

As a further dimension, I examine the prevalence of my five focal topics over time. As described in detail in Section 4.3, I expect topic prevalence to vary strongly over time, due to the short-lived character of media attention. To verify this empirical prediction, I split the observation period into 50 bins as described in Section 4.5, then first calculate topic frequencies for each bin, and finally recalculate topic representations for every time window. This allows me (a) to identify temporal patterns in the frequencies of every individual topic, and (b) to examine whether the topic is discussed differently over time (i.e., whether different vocabulary is used to refer to a topic). Figure 4.5 shows the temporal evolution of topic frequencies with the five focal topics once again highlighted in color. Starting from the origin of the timeline, the first major peak happens for the topic "Banking crisis" (see golden line) in 2009. This spike in the first quarter of 2009 turns out to be a repercussion of the 2007-2008 global financial crisis: on February 27, 2009, the *Dow Jones* closed at its lowest value since 1997 and news reporting around that time evolved around terms like "crisis", "bailout", "wall street", and so on. The second major peak of the golden line (beginning of 2010) in Figure 4.5 again pertains to the aftermath of the financial crisis. At that time, the main topic in the media was that then US President Obama was pushing for measures to regulate banks in order to prevent a repetition of the financial market collapse.[9] Next, I examine the spikes that happen in late 2012 for the topics *"Tax cuts"* and *"Capital markets"*. Skimming through representative articles for the two topics at that time reveals that in both cases, the so-called "fiscal cliff" was the issue that drove media coverage. The "fiscal cliff" refers to a looming *de facto* tax increase in the USA that was scheduled to take effect on December 31, 2012 due to expiring temporary tax breaks. Articles belonging to the topic *"Tax cuts"* mainly describe efforts by industry representatives and lobbyists to avoid that tax increase[10], whereas those articles belonging to the topic *"Capital markets"* describe the relief at the stock markets, when a last-minute deal was negotiated in the US congress on January 01, 2013 to avert the tax increases[11]. A similar co-movement between these two topics shows at the end of 2017, when the Trump administration's *Tax Cuts and Jobs Act* (effective as of January 01, 2018) and the

[9]For a representative article of the topic *"Banking crisis"* in this time period as suggested by my model, see: https://www.nytimes.com/2010/02/02/business/02sorkin.html (last access: April 11, 2023).

[10]An exemplary article for this type of news can be found here: https://www.washingtonpost.com/business/economy/executives-push-for-fiscal-cliff-deal-even-if-their-tax-concerns%2Dhave%2Dto-wait/2012/12/12/3647ccbe%2D4488-11e2-8061-253bccfc7532_story.html (last access: April 11, 2023).

[11]For a representative example, see: https://www.nytimes.com/2013/01/01/business/daily-stock-market%2Dactivity.html (last access: April 11, 2023).

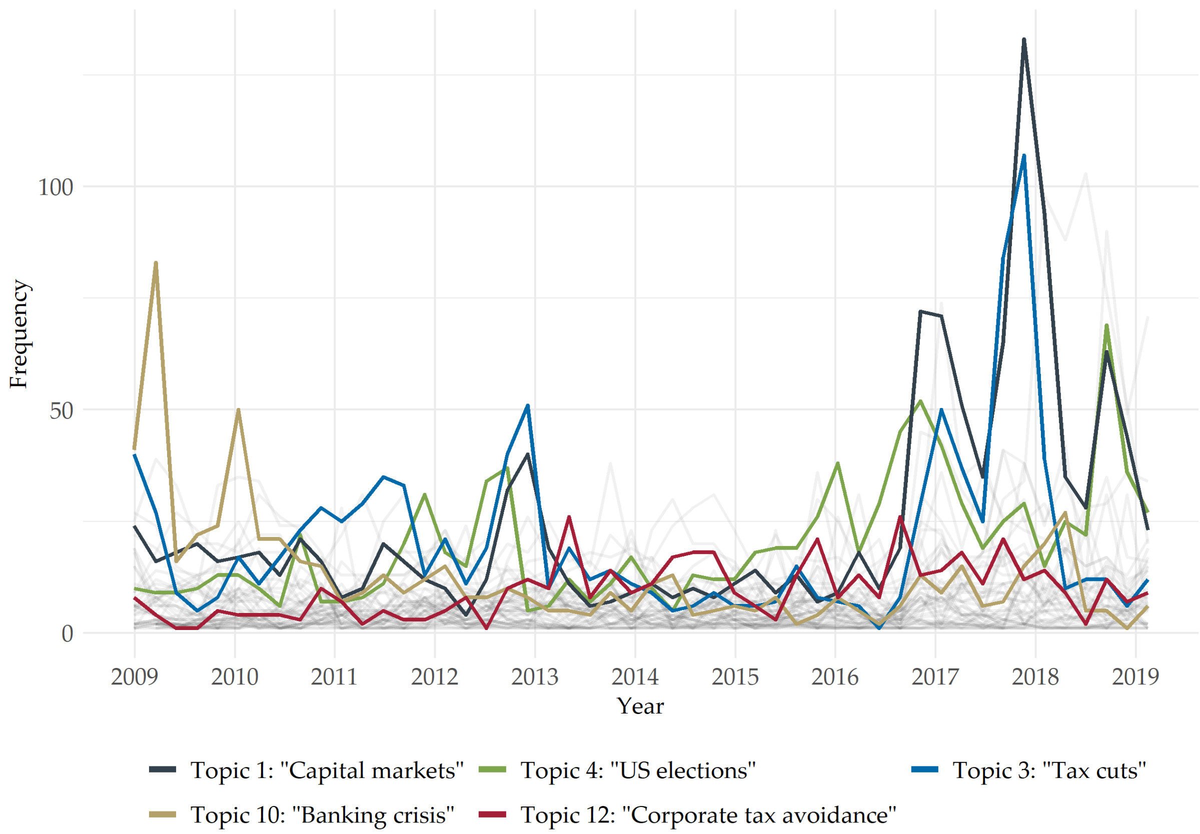


Figure 4.5: Topics over time

corresponding stock market reactions were heavily discussed by the press.[12] Interestingly, the topic *"Capital market"* also shares spikes with other topics, such as the *"US elections"* in late 2016. In Section 4.4, I identified an anomaly in the volume of *IBD* articles at the end of 2016 and the end of 2017. Looking at the topics over time for *IBD* alone (see Appendix C.6) and skimming through some of the corresponding articles reveals that it is the news about stock market reactions to the presidential elections 2016 (first spike) and the stock market reactions to the *Tax Cuts and Jobs Act* (second spike) that cause these anomalies. Finally, it is rather surprising and against my a priori expectations that the topic *"Corporate tax avoidance"* shows no extraordinary pattern, such that from pure visual inspection of Figure 4.5, it would not be possible to locate major tax leaks in the time series such as *LuxLeaks* (November 2014) or *Paradise Papers* (November 2017).

Regarding the question of how topic representations eventually change over time, it is most eye-catching to look at the topic *"US elections"*. While the global topic representation (see Table 4.4) is dominated by broader terms such as "republican", "democratic", "campaign", or "can-

[12] For representative articles, see: https://www.nytimes.com/2017/09/28/business/trump%2Dtax%2Dbusinesses.html or https://www.washingtonpost.com/news/business/wp/2018/01/04/the-dow-jones%2Dindustrial-average-tops-25000-for-first-time-continuing-its-history-making-rise/ (last access: April 11, 2023).

didates", the topic representations for the individual intervals capture short-term trends in the news reporting and mainly contain names of politicians that dominate the discourse in the respective time window. This allows me to sketch a detailed timeline of the 2016 US presidential elections. Table 4.5 shows the topic representations of *"Topic 4: US elections"* for the relevant time intervals around the US elections in November 2016. For a complete list of all topic representations between 2009 and 2019, see Appendix C.7.

Table 4.5: Time-specific topic representations for "Topic 4: US elections" (extract)

Timestamp	Time-specific topic representation (Top 5 words or bigrams)
2014-12-28	huckabee, iowa, christie, santorum, mr santorum
2015-03-13	huckabee, mr walker, mr paul, republican, walker
2015-05-28	sanders, jindal, walker, iowa, mr sanders
2015-08-11	cooper, sanders, malley, clinton, applause
2015-10-25	rubio, applause, thank, cruz, senator
2016-01-09	applause, rubio, sanders, cruz, clinton
2016-03-24	sanders, blitzer, clinton, applause, senator sanders
2016-06-08	mr weaver, trump, priebus, convention, weaver
2016-08-22	clinton, trump, wallace, holt, secretary clinton
2016-11-05	trump, president elect, clinton, elect, mr trump

Looking at the time span presented in Table 4.5, the topic representations mainly include names of candidates for the primaries as top words. These top words map quite well how the list of candidates in the 2016 presidential primaries is shrinking as the election date approaches: In the early stages, the list includes names of candidates who soon withdrew their candidacies (e.g., Huckabee, O'Malley, Bush, Jindal). In the final phase of the primaries, the set of names in the topic representations narrows down to the remaining and most promising candidacies of (Bernie) Sanders, (Ted) Cruz, or (Marco) Rubio, until finally only (Hillary) Clinton and (Donald) Trump remain in the topic representations. While I acknowledge that articles on the US election campaign discuss the topic of taxes only marginally and therefore do not provide much substantive insight in this regard, considering the chronological development of this exemplary topic is nevertheless a worthwhile endeavour since it nicely showcases the ability of the BERTopic method to track changes within a topic over time.

4.6.4 Alternative model specifications

All results presented throughout this section are based on my focal model specification with parameter settings as described in Section 4.5. Table 4.6 shows two alternative model specifications with variations in the *n_neighbors* and the *n_components* parameters of the UMAP algorithm, which both show comparable and robust results with regard to topic interpretability and sizes.

In further robustness checks, I also ran several alternative transformer models (e.g., "all-mpnet-base-v2" and "all-distilroberta-v1") that work with higher-dimensional embeddings (768 dimensions) and with a maximum sequence length of 512 compared to "all-MiniLM-L6-v2" (384 dimensions and maximum sequence length of 256). Since this did not yield noticeable improvements in the quality of the resulting topics (see Appendix C.8), I discarded these specifications in favor of the more lightweight and faster "all-MiniLM-L6-v2" transformer model. Further, I varied the minimum cluster size (*min_cluster_size*) of the HDBSCAN algorithm between 10 and 200. Smaller values of *min_cluster_size* resulted in too many extremely small, cluttered, and therefore uninterpretable topics, larger values resulted in only very few large (and hence also uninterpretable) topic clusters. For this reason, I set the value to 100 in all reported alternative specifications in Table 4.6.

Table 4.6: Overview over topic model specifications and summarized results

		Focal model	**Variant A**	**Variant B**
SBERT	*transformer_model*	all-MiniLM-L6-v2	all-MiniLM-L6-v2	all-MiniLM-L6-v2
UMAP	*n_neighbors*	30	100	100
	n_components	5	5	10
HDBSCAN	*min_cluster_size*	100	100	100
	min_samples	100	100	100
Topic descriptives	*# of outliers*	15,210	15,833	16,575
	# of topics	51	46	45
	Average topic size	381.1	409.0	401.6
Sizes of focal topics	*"Capital markets"*	1,256	1,153	1,347
	"US elections"	1,002	1,019	915
	"Tax cuts"	1,044	824	855
	"Banking crisis"	644	475	723
	"Corporate tax avoidance"	480	575	495

4.7 Conclusion

In this research, I analyze the content of 34,645 news articles mentioning a corporation together with the term "tax". To do this, I apply BERTopic, a state-of-the-art neural topic modeling approach (Grootendorst, 2022). This study contributes to the literature in two ways: First, it provides substantive insights regarding the question what newspapers report about when they talk about firms in a tax context. This sheds some light on what themes seem to be relevant for newspapers and their readership, and on how the media carry out their watchdog role when it comes to tax-related corporate activities. Second, using my text corpus of news articles about corporate tax activities as an application context, the study demonstrates the potential of automated topic modeling techniques in uncovering content-related information from media coverage data. Considering that novel topic modeling approaches such as BERTopic have not yet been applied in business-related academic publications on firm media coverage, this study makes a case for a stronger integration of modern methods from computational linguistics into the methods toolbox of researchers in this discipline.

4.7.1 Lessons learned from a substantive perspective

The first thing to note regarding the question of what newspapers report on when they mention companies in a tax context is that the field of topics is much broader than initially assumed. The largest topic in the focal specification as well as in most alternative specifications turns out to concern is the broad field of capital market news – a field where corporate taxes play an important, yet subordinate role. Other large topics span from news about current political affairs such as the US elections to geopolitical issues such as the trade with China, and from energy sources to news about the housing and labor markets. News about the issue of corporate tax avoidance – a topic which I expected to be one of the largest ones a priori – shows to be comparably small and is only the dominant topic in 2.5 percent of the articles (compared to the capital markets with over 6.5 percent). Interesting findings also emerge when looking at the topic frequencies in the individual news outlets. As expected, I find substantial differences, especially regarding the business specialist newspaper *Investor's Business Daily*, where capital market news make up a share of about 20 percent. Political topics, such as the US elections, on the other hand are extremely small compared to the daily broadsheet newspapers. Also, it is interesting to see that among all four newspapers considered, *The New York Times* has the highest share of articles dealing with corporate tax avoidance. Of course, it is difficult, if not impossible, to make a judgment on this basis as to whether or not the media are paying sufficient attention to the socially highly relevant issue of corporate tax avoidance. What is undeniably true, however, is that the issue of tax avoidance does not seem to dominate the media to the extent that other topics do, even if the sample of media coverage is restricted to articles that mention the word "tax" with a firm name. Finally, looking at the development of tax-related firm media coverage over time, it is events related to US politics that stand out most and that are most influential to media coverage. Two major jumps in my sample of media coverage can be traced back to events in US politics, the first being the election of Donald Trump as US president in November 2016 and the second being his corporate tax reform from January 2018, which had major implications to companies and the capital markets.

At this point, it seems appropriate to relate the results presented here to our approach in Chapter 2. The fact that the newspaper articles in my sample cover a broader range of topics than originally expected may raise concerns among the readers of this thesis about the appropriateness of our article volume variable. Specifically, doubts might arise as to whether our article volume variable really measures tax-related media attention or just general media attention ("buzz") that mentions taxes. I want to address this potential limitation in two ways: First, the assignment of articles to a topic cluster in this study is a binary decision and it only reflects the top topic in an article. This may create the false impression, that many articles do not deal with taxes at all. However, articles likely cover more than one topic, and even articles from topic clusters that seem to have only little direct connection to corporate taxes (e.g., energy sources or the housing market), may cover corporate taxes as a secondary topic. Second, while our article volume variable is tax-specific (and not tax *avoidance*-specific), our focus in Chapter 2 is on the interaction between volume and negativity, with our negativity variable being tax *avoidance*-specific. To validate the appropriateness of our negativity measure, I calculate negativity scores as defined in Section 2.4 separately for the articles of each topic cluster. I find that among the significant topics from the focal model, the topic *"Corporate tax avoidance"* has the highest negativity score with respect to tax avoidance, and it is almost twice as high as the grand mean article negativity. I take this as an indication that the selected negativity measure from Chapter 2 works and that possible concerns that may remain regarding the volume variable do not hold for the negativity and the interaction.

4.7.2 Lessons learned from a methodological perspective

Newspaper articles are a rich data source and it is therefore no coincidence that the literature frequently uses them to measure public attention. However, my literature review suggests that especially in the field of business and management research, the full potential of newspaper articles does not appear to be fully exploited as of yet. Often, researchers limit themselves to either sticking with crude count-based measures to capture the content of a text, or to manually inspecting texts for their content, which severely restricts the scalability to larger text corpora. It seems that the discipline so far neglects the recent developments in computational linguistics when it comes to extracting content information from company media attention.

My results suggest that this is a missed opportunity. Using the neural topic modeling technique BERTopic (Grootendorst, 2022), this study succeeds in identifying human-interpretable themes that are addressed in a large corpus of nearly 35,000 newspaper articles. With very broad prior expectations, I manage to identify well-defined topics, whose occurrences over time I can relate to events that happened over the observation period. By looking at the topic representations of the exemplary topic *"US elections"* art different points in time, I show that BERTopic is able to capture how topics evolve over time and what major themes drive media attention in different time periods. Further, by looking at different newspapers, I show that the method is able to model heterogeneity in topics between different classes of texts. Abstracting from my specific application, various use cases for the method are conceivable along the research pipeline when studying media coverage of firms:

First, BERTopic can be used early in the research process as a screening tool to identify potential anomalies in text corpora that are prohibitively large for manual reading. In such cases, it can be useful to see which topics show unusual patterns over time, and looking at a handful of representative articles (rather than potentially hundreds and thousands of arbitrary articles) can then help determine whether or not there is a plausible explanation to it.

Second, instead of using keyword searches to identify potentially relevant articles for a selected research question, one could use BERTopic to narrow down the list of potentially relevant articles. Consider for example the study by Beattie et al. (2021), who make the assumption that all articles that contain the words "safety" and "recall" concern product recalls. One could raise the concern here that the word "safety" is used in many other situations as well, and that "recall" could also mean "remember". This keyword rule could therefore potentially lead to unrelated articles ending up in the sample. BERTopic's ability to also consider the context of words make it a promising strategy to overcome this shortcoming of keyword-based approaches and to identify relevant articles more reliably.

Third, many studies use the volume of news articles as an independent variable to explain some outcome (e.g., Nikolaeva and Bicha, 2011; Solomon, Soltes, and Sosyura, 2014; Van Heerde, Gijsbrechts, and Pauwels, 2015). Often, this implicitly assumes an effect that is homogeneous (e.g., Nikolaeva and Bicha, 2011) or, at most, moderated by the tone of the reporting (e.g., Van Heerde, Gijsbrechts, and Pauwels, 2015). However, depending on the context of the respective research question, it is possible that different types of news article content affect the outcome in a heterogeneous way. Once articles are clustered and assigned to well-defined topics using BERTopic, it could be a promising strategy to use cluster memberships as moderator variables to empirically test for heterogeneous effects across different topics.

4.7.3 Limitations

I acknowledge that this study comes with some limitations that could and should be addressed, at least in part, by future research. First of all, my study is purely descriptive in the sense that I remain agnostic about how media outlets and journalists select the topics that they write about. What I describe with my topic model is simply the outcome of an agenda-setting process in publishing houses, about which I can make no statements. In future research, it may be also interesting to think about antecedents of topic choices on the part of publishers. Next, all of my analyses are based on binary topic assignments, meaning that every article is assigned to no more than one topic cluster, namely the one with the highest topic probability. While this helps provide clarity to the results, I lose potentially valuable information about secondary topics in articles. It could be worthwhile for future research to look deeper into the probabilities for other than the top topics in an article. Another way to identify potentially different subtopics within one article could be to split articles into smaller units, such as individual paragraphs, or sentences. Applying BERTopic to these sub-units of an article might then reveal interesting findings regarding the topic diversity within documents. At the same time, such an approach would yield shorter documents, thus alleviating concerns that might arise due to the truncation of articles to the first 256 (or 512) tokens. Finally, several decisions throughout this study are following subjective criteria. For example, I assign topic labels based on my personal perception and interpretation of the topic representations, and I select parameters to the model based on my perception of how well-defined and interpretable the resulting topics are. I think that this approach can be justified in the context of this research, since one goal of the study is to automate the identification of topics in prohibitively large text data, which was frequently done manually (and hence also subjective) in prior research for smaller text corpora. Nevertheless, future research could attempt to develop objective decision criteria on which to formally validate the results of the topic model.

5

Conclusion

In recent years, companies have increasingly emphasized their commitment in the area of corporate social responsibility (CSR) and literature suggests that consumers are growing increasingly concerned with CSR (Nickerson et al., 2022). In view of this development, it is striking that at the same time, large corporations, including some that otherwise portray themselves as particularly socially responsible, are caught evading taxes. Take *Starbucks*, for example: The coffeehouse chain that puts a special emphasis on its commitment to all areas of sustainability (environmental, social, and governance)[1] has been repeatedly scrutinized in news reports about aggressive tax avoidance activity (e.g., Bergin, 2012; Neate, 2019). This dissonance between visible and high-profile CSR strategies on the one hand and questionable tax practices on the other (and Starbucks is by no means an isolated case) raises several important questions. The goal of this thesis was to address some of these questions. The results of the studies presented in Chapters 2, 3, and 4 of this dissertation provide relevant insights for firms, public policy makers, and society at large. In the following, I briefly reiterate the main findings of each chapter individually before I integrate the results into a larger picture. Table 5.1 summarizes the core aspects of all three studies.

Chapter 2 of this thesis focused on the implications of media attention to tax avoidance for different actors in the market. Using a comprehensive data set consisting of (social) media attention, firm financial information, stock market data, as well as consumer-based brand metrics, my co-authors and I examined how unanticipated increases in the volume and negativity of tax-related firm media coverage affects investor and consumer behavior. We found that consumers notice tax-related news coverage, which manifests itself in higher brand attention and a lower brand strength following an increase in negative newspaper coverage. In terms of stock market reactions, we showed that increased tax-related media attention is not penalized by investors to the extent that stock prices drop. What we have seen, however, is an increase in trading volume, suggesting that investors indeed react to negative tax media coverage, albeit in a heterogeneous way.

Chapter 3 put the focus on the interplay between corporate social performance, tax avoidance, and firm financial performance. Specifically, I investigated whether refraining from aggressive tax avoidance can help a firm in building goodwill that shields it from negative consequences of socially irresponsible actions in non-tax areas. What I found in this study supports

[1]See https://www.starbucks.com/responsibility/reporting-hub/ (last access: April 11, 2023)

	Chapter 2	**Chapter 3**	**Chapter 4**
Title	*Corporate Tax Avoidance in the Spotlight – How its (Social) Media Coverage Affects Firm Value, Brand Metrics, and Trading Volume*	*Paying Taxes to Calm Tempers? The Moderating Role of Effective Tax Rates on Value Implications of Corporate Misdeeds*	*Exploring the Discourse of Corporate Taxes: A BERTopic Analysis of Tax-Related Firm Media Coverage*
Research question	How do investors and consumers react to tax-related media coverage?	Can tax payments shield a firm against negative financial consequences of (non-tax) CSI?	Which topics do the news media talk about when they mention a firm in the context of taxes?
Data	• Stock market data • (Social) media attention • Accounting data • Brand attention/strength	• Accounting data • CSR/CSI data	• Tax-related firm media coverage (newspapers)
Method	Stock return response model	Fixed-effects panel regression	BERTopic (neural topic model)
Main findings	• Consumers care if they find out about corporate tax avoidance through the media and brand strength suffers • Investors interpret increased media attention to corporate tax avoidance in a heterogeneous way: some sell the stock, but just as many buy the stock	• CSI negatively affects a firm's financial performance • The negative effect of CSI is positively moderated by the effective tax rate, suggesting that refraining from tax avoidance protects a firm from negative consequences of (non-tax) CSI	• Topics that newspapers discuss are more diverse than expected • Corporate tax avoidance plays minor role in public discourse • Novel topic modeling techniques are promising tools to reliably identify common themes in large collections of newspaper articles

Table 5.1: Overview of the chapters and their main results

my a priori expectation of this insurance effect. I documented a negative effect of (non-tax) corporate social irresponsibility (CSI) on firm performance as measured by Tobin's q, and I found evidence that this negative effect is dampened if firms have a higher effective tax rate, i.e., if they pay more in taxes relative to their pre-tax income.

Chapter 4 concerned the role of the news media in reporting on tax-related corporate activities and addressed the question which topics newspapers discuss when they mention firms in the context of taxes. In this chapter, I employed *BERTopic*, a neural topic modeling technique, to study a large corpus of almost 35,000 news articles mentioning firms in conjunction with the term "tax". Interesting insights evolved from my analyses, for example that there is significant heterogeneity in topic prevalences across news outlets, and that topic prevalences vary strongly over time. I found the issue of corporate tax avoidance to be less pronounced in the press than initially expected, and that topics are generally very diverse. Another major finding from the study was that machine learning-based topic modeling techniques are able to reliably identify common themes in firm media coverage in an automated way – something that business-related research to date has mostly done either manually for data sets of very limited size, or using keyword-based heuristics that do not yield as detailed results.

This thesis investigates corporate tax avoidance from a variety of different perspectives. A common theme throughout all chapters is the relevance of tax avoidance in different contexts and for a wide variety of stakeholders. First, *consumers* and *society* at large care about tax avoidance, as is reflected (a) in countless social media postings and newspaper articles about the topic, and (b) in the increased brand attention and reduced brand strength induced by unanticipated changes in tax-related media attention. Second, tax avoidance also seems to matter for *investors*, as the changes in trading behavior suggest that we find following increases in tax-related (social) media attention in Chapter 2. Even if the media coverage does not lead to an immediate drop in the share price of the tax avoiding firm, the increased trading volume nevertheless shows a disagreement among investors about how future cash flows are affected by the media coverage and the resulting loss in brand strength. Moreover, the dissertation shows that in addition to investors and consumers, *managers* also have an interest in reconsidering their tax planning decisions. This is not only because the brand strength damage might lead to adverse effects on firm value in the long-run, but also because refraining from tax avoidance may build goodwill among customers that can serve as a shield against future CSI incidents (which, unlike tax avoidance, are not always the result of a deliberate management decision). Managers should consider rethinking the role of tax planning in their companies and see it not just as a back-office function, but as one that can potentially have direct implications for a brand. In all of this, the *media* play a crucial role as intermediaries in reducing information asymmetries between companies and the public and in increasing transparency. It is the *newspapers* in particular that have a significant influence on the public's perception of corporate tax behavior. Transparency is also what several recent public policy measures are based on that aim to curb tax avoidance (e.g., the EU's country-by-country reporting directive). This thesis provides relevant findings for *public policy makers* in that it shows that consumers in fact already know and seemingly care about corporate tax avoidance, but that this does not seem to exert enough pressure on firms to induce sustainable change in their tax behaviour. It can therefore to be assumed that those measures that rely only on transparency and public knowledge about tax avoidance will not have a significant effect in curbing tax avoidance.

In conclusion, this dissertation examined the issue of corporate tax avoidance, a topic that is of utmost societal relevance, from various angles. The thesis derived insightful findings in many respects – for managers, for policy makers, and for society in general – and can thus inform the public discourse on how to deal with corporate tax avoidance. Corporate tax avoidance is a major challenge of our time, and with this dissertation I hope to make a contribution to finding appropriate answers to it.

References

Ad Fontes Media "Interactive Media Bias Chart," (2023) https://adfontesmedia.com/interactive-media-bias-chart/, (accessed April 11, 2023).

Ahern, Kenneth R. and Denis Sosyura (2015), "Rumor Has It: Sensationalism in Financial Media," *The Review of Financial Studies*, 28 (7), 2050–2093.

Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research*, 37 (2), 203–214.

Ailawadi, Kusum L., Scott A. Neslin, Y. Jackie Luan, and Gail Ayala Taylor (2014), "Does retailer CSR enhance behavioral loyalty? A case for benefit segmentation," *International Journal of Research in Marketing*, 31 (2), 156–167.

Avi-Yonah, Reuven S (2014), "Corporate Taxation and Corporate Social Responsibility," *NYU Journal of Law & Business*, 11 (1), 1–29.

Backhaus, Max and Marc Fischer (2016), "Brand Damage from Product Harm and Corporate Social Irresponsibility: How Deep and How Long?," *Marketing Science Institute Working Paper Series*, 16 (133), 1–63.

Bamber, Linda Smith, Orie E. Barron, and Thomas L. Stober (1999), "Differential Interpretations and Trading Volume," *The Journal of Financial and Quantitative Analysis*, 34 (3), 369–386.

Barkemeyer, Ralf, Christophe Faugère, Olivier Gergaud, and Lutz Preuss (2020), "Media attention to large-scale corporate scandals: Hype and boredom in the age of social media," *Journal of Business Research*, 109, 385–398.

Bearden, William, Richard Netemeyer, and Kelly Haws (2011), *Handbook of Marketing Scales: Multi-Item Measures for Marketing and Consumer Behavior Research* Thousand Oaks, California, 3rd edition.

Beattie, Graham, Ruben Durante, Brian Knight, and Ananya Sen (2021), "Advertising Spending and Media Bias: Evidence from News Coverage of Car Safety Recalls," *Management Science*, 67 (2), 698–719.

Becker-Olsen, Karen L., B. Andrew Cudmore, and Ronald Paul Hill (2006), "The impact of perceived corporate social responsibility on consumer behavior," *Journal of Business Research*, 59 (1), 46–53.

Bednar, Michael K., E. Geoffrey Love, and Matthew Kraatz (2015), "Paying the Price? The Impact of Controversial Governance Practices on Managerial Reputation," *The Academy of Management Journal*, 58 (6), 1740–1760.

Bellman, Richard E. (1961), *Adaptive Control Processes: A Guided Tour* Princeton University Press.

Bergin, Tom (2012), "Special Report - How Starbucks avoids UK taxes," *Reuters* https://www.reuters.com/article/us-britain-starbucks-tax-idUKBRE89E0EX20121015, (accessed April 11, 2023).

Bhagwat, Yashoda, Nooshin L. Warren, Joshua T. Beck, and George F. Watson (2020), "Corporate Sociopolitical Activism and Firm Value," *Journal of Marketing*, 84 (5), 1–21.

Blaufus, Kay, Axel Möhlmann, and Alexander N. Schwäbe (2019), "Stock price reactions to news about corporate tax avoidance and evasion," *Journal of Economic Psychology*, 72, 278–292.

Blei, David M., Andrew Y. Ng, and Michael I. Jordan (2003), "Latent dirichlet allocation," *The Journal of Machine Learning Research*, 3, 993–1022.

Bouquet, Cyril and Yuval Deutsch (2008), "The Impact of Corporate Social Performance on a Firm's Multinationality," *Journal of Business Ethics*, 80 (4), 755–769.

Bushee, Brian J. (1998), "The influence of institutional investors in myopic R&D investment behavior," *Accounting Review*, 73 (3), 305.

Bushee, Brian J., John E. Core, Wayne Guay, and Sophia J.w. Hamm (2010), "The Role of the Business Press as an Information Intermediary," *Journal of Accounting Research*, 48 (1), 1–19.

Business Roundtable "Business Roundtable Redefines the Purpose of a Corporation to Promote 'An Economy That Serves All Americans'," (2019) https://www.businessroundtable.org/business-roundtable-redefines-the-purpose-of-a-corporation-to-promote-an-economy%2Dthat%2Dserves%2Dall%2Damericans, (accessed April 11, 2023).

Bénabou, Roland and Jean Tirole (2010), "Individual and Corporate Social Responsibility," *Economica*, 77 (305), 1–19.

Cadwalladr, Carole (2018), "'I made Steve Bannon's psychological warfare tool': meet the data war whistleblower," *The Guardian* https://www.theguardian.com/news/2018/mar/17/data-war-whistleblower-christopher-wylie-faceook-nix-bannon-trump, (accessed April 11, 2023).

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

Carroll, Craig E. and David L. Deephouse "The foundations of a theory explaining organizational news: The VT4 Framework of Organizational News Content and five levels of influence on its production," Josef Pallas, Lars Strannegård, and Stefan Jonsson, editors, "Organizations and the Media: Organizing in a mediatized world," pages 81–95, London: Routledge, 1st edition (2014).

Chatterjee, Arijit and Donald C. Hambrick (2011), "Executive Personality, Capability Cues, and Risk Taking: How Narcissistic CEOs React to Their Successes and Stumbles," *Administrative Science Quarterly*, 56 (2), 202–237.

Chen, Shannon, Kathleen Schuchard, and Bridget Stomberg (2019), "Media Coverage of Corporate Taxes," *Accounting Review*, 94 (5), 83–116.

Chen, Xin, Wei He, Libin Tao, and Jianfeng Yu (2023), "Attention and Underreaction-Related Anomalies," *Management Science*, 69 (1), 636–659.

Chollet, François and Joseph J. Allaire (2018), *Deep Learning with R* Shelter Island, NY: Manning Publications, 1st edition.

Chung, Kee H. and Stephen W. Pruitt (1994), "A Simple Approximation of Tobin's q," *Financial Management*, 23 (3), 70–74.

Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises," *Journal of Marketing*, 77 (2), 58–77.

Cohen, Patricia (2021), "No Federal Taxes for Dozens of Big, Profitable Companies," *The New York Times* https://nyti.ms/3ufN6R8, (accessed April 11, 2023).

Col, Burcin, Art Durnev, and Alexander Molchanov (2018), "Foreign Risk, Domestic Problem: Capital Allocation and Firm Performance Under Political Instability," *Management Science*, 64 (5), 2102–2125.

Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O'Connor (2018), "Improving Consumer Mindset Metrics and Shareholder Value through Social Media: The Different Roles of Owned and Earned Media," *Journal of Marketing*, 82 (1), 37–56.

Davis, Angela K., David A. Guenther, Linda K. Krull, and Brian M. Williams (2016), "Do Socially Responsible Firms Pay More Taxes?," *The Accounting Review*, 91 (1), 47–68.

Deephouse, David L (2000), "Media Reputation as a Strategic Resource: An Integration of Mass Communication and Resource-Based Theories," *Journal of Management*, 26 (6), 22.

Desai, Mihir A and Dhammika Dharmapala (2009), "Corporate Tax Avoidance and Firm Value," *The Review of Economics and Statistics*, 91 (3), 537–546.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2019), "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *arXiv:1810.04805 [cs.CL]* http://arxiv.org/abs/1810.04805, (accessed April 11, 2023).

Dixon-Fowler, Heather R., Alan E. Ellstrand, and Jonathan L. Johnson (2013), "Strength in numbers or guilt by association? Intragroup effects of female chief executive announcements," *Strategic Management Journal*, 34 (12), 1488–1501.

Drake, Michael S., Nicholas M. Guest, and Brady J. Twedt (2014), "The Media and Mispricing: The Role of the Business Press in the Pricing of Accounting Information," *The Accounting Review*, 89 (5), 1673–1701.

Du, Shuili, C. B. Bhattacharya, and Sankar Sen (2007), "Reaping relational rewards from corporate social responsibility: The role of competitive positioning," *International Journal of Research in Marketing*, 24 (3), 224–241.

Durand, Rodolphe and Jean-Philippe Vergne (2015), "Asset divestment as a response to media attacks in stigmatized industries," *Strategic Management Journal*, 36 (8), 1205–1223.

Dutta, Sujay and Chris Pullig (2011), "Effectiveness of corporate responses to brand crises: The role of crisis type and response strategies," *Journal of Business Research*, 64 (12), 1281–1287.

Dwenger, Nadja and Lukas Treber (2022), "Shaming for Tax Enforcement," *Management Science*, 68 (11), 8202–8233.

Dyck, Alexander, Natalya Volchkova, and Luigi Zingales (2008), "The Corporate Governance Role of the Media: Evidence from Russia," *The Journal of Finance*, 63 (3), 1093–1135.

Dyck, Alexander and Luigi Zingales "The Corporate Governance Role of the Media," "The Right to Tell : The Role of Mass Media in Economic Development," pages 107–137, Washington, DC: The World Bank Institute (2002).

Dyreng, Scott D., Michelle Hanlon, and Edward L. Maydew (2008), "Long-Run Corporate Tax Avoidance," *Accounting Review*, 83 (1), 61–82.

Dyreng, Scott D., Jeffrey L. Hoopes, and Jaron H. Wilde (2016), "Public Pressure and Corporate Tax Behavior," *Journal of Accounting Research*, 54 (1), 147–186.

Eilert, Meike, Satish Jayachandran, Kartik Kalaignanam, and Tracey A. Swartz (2017), "Does It Pay to Recall Your Product Early? An Empirical Investigation in the Automobile Industry," *Journal of Marketing*, 81 (3), 111–129.

Eilert, Meike and Abigail Nappier Cherup (2020), "The Activist Company: Examining a Company's Pursuit of Societal Change Through Corporate Activism Using an Institutional Theoretical Lens," *Journal of Public Policy & Marketing*, 39 (4), 461–476.

EPG Economic and Strategy Consulting "Business Backs Education - Creating a baseline for Corporate CSR Spend on Global Education Initiatives," (2015) https://www.economicpolicygroup.com/publication/business-backs-education-report-launch/, (accessed April 11, 2023).

Etter, Michael, Davide Ravasi, and Elanor Colleoni (2019), "Social Media and the Formation of Organizational Reputation," *Academy of Management Review*, 44 (1), 28–52.

European Commission "State aid: Irish tax treatment of Apple is illegal," (2016) https://ec.europa.eu/commission/presscorner/detail/en/IP_16_2923, (accessed April 11, 2023).

European Commission "Public country-by-country reporting," (2021) https://ec.europa.eu/info/business-economy-euro/company-reporting-and-auditing/company-reporting/public-country-country-reporting_en, (accessed April 11, 2023).

Fama, Eugene F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 25 (2), 383–417.

Fama, Eugene F. and Kenneth R. French (1993), "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33 (1), 3–56.

Financial Times Editorial Board "Corporate bailouts should come with strings," (2020) https://on.ft.com/37hsn6G, (accessed April 11, 2023).

Flammer, Caroline (2013), "Corporate Social Responsibility and Shareholder Reaction: The Environmental Awareness of Investors," *Academy of Management Journal*, 56 (3), 758–781.

Foerderer, Jens and Sebastian W. Schuetz (2022), "Data Breach Announcements and Stock Market Reactions: A Matter of Timing?," *Management Science*, 68 (10), 7298–7322.

Friedman, Milton (1970), "A Friedman doctrine - The Social Responsibility Of Business Is to Increase Its Profits," *The New York Times* https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html, (accessed April 11, 2023).

Gal-or, Esther, Tansev Geylani, and Tuba Pinar Yildirim (2012), "The Impact of Advertising on Media Bias," *Journal of Marketing Research*, 49 (1), 92–99.

Gallemore, John, Edward L. Maydew, and Jacob R. Thornock (2014), "The Reputational Costs of Tax Avoidance," *Contemporary Accounting Research*, 31 (4), 1103–1133.

Gelles, David and David Yaffe-Bellany (2019), "Shareholder Value Is No Longer Everything, Top C.E.O.s Say," *The New York Times* https://www.nytimes.com/2019/08/19/business/business-roundtable-ceos-corporations.html, (accessed April 11, 2023).

Gentzkow, Matthew and Jesse M. Shapiro (2006), "Media Bias and Reputation," *Journal of Political Economy*, 114 (2), 280–316.

Godfrey, Paul C., Craig B. Merrill, and Jared M. Hansen (2009), "The relationship between corporate social responsibility and shareholder value: an empirical test of the risk management hypothesis," *Strategic Management Journal*, 30 (4), 425–445.

Golder, Peter N., Marnik G. Dekimpe, Jake T. An, Harald J. van Heerde, Darren S.U. Kim, and Joseph W. Alba (2022), "Learning from Data: An Empirics-First Approach to Relevant Knowledge Generation," *Journal of Marketing*, 87 (3), 319–336.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera (2021), "Social media, sentiment and public opinions: Evidence from #Brexit and #USElection," *European Economic Review*, 136, 1–22.

Graf-Vlachy, Lorenz, Abbie Griffith Oliver, Richard Banfield, Andreas König, and Jonathan Bundy (2020), "Media Coverage of Firms: Background, Integration, and Directions for Future Research," *Journal of Management*, 46 (1), 36–69.

Graves, Samuel B. and Sandra A. Waddock (1990), "Institutional ownership and control: implications for long-term corporate strategy," *Academy of Management Executive*, 4 (1), 75–83.

Griffin, Jennifer J. and John F. Mahon (1997), "The Corporate Social Performance and Corporate Financial Performance Debate: Twenty-Five Years of Incomparable Research," *Business & Society*, 36 (1), 5–31.

Groening, Christopher and Vamsi Krishna Kanuri (2013), "Investor reaction to positive and negative corporate social events," *Journal of Business Research*, 66 (10), 1852–1860.

Groening, Christopher, Vikas Mittal, and Yan "Anthea" Zhang (2016), "Cross-Validation of Customer and Employee Signals and Firm Valuation," *Journal of Marketing Research*, 53 (1), 61–76.

Grootendorst, Maarten (2022), "BERTopic: Neural topic modeling with a class-based TF-IDF procedure," *arXiv:2203.05794 [cs.CL]* https://arxiv.org/abs/2203.05794, (accessed April 11, 2023).

Hachten, William A. (1963), "The Press as Reporter and Critic of Government," *Journalism Quarterly*, 40 (1), 12–18.

Hambrick, Donald C. and Adam J. Wowak (2021), "CEO Sociopolitical Activism: A Stakeholder Alignment Model," *Academy of Management Review*, 46 (1), 33–59.

Hanlon, Michelle and Joel Slemrod (2009), "What does tax aggressiveness signal? Evidence from stock price reactions to news about tax shelter involvement," *Journal of Public Economics*, 93 (1-2), 126–141.

Hansen, Nele, Ann-Kristin Kupfer, and Thorsten Hennig-Thurau (2018), "Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands," *International Journal of Research in Marketing*, 35 (4), 557–574.

Hanssens, Dominique M., Leonard J. Parsons, and Randall L. Schultz (2001), *Market Response Models: Econometric and Time Series Analysis* Norwell, Massachusetts: Kluwer Academic Publishers, 2nd edition.

Harcup, Tony and Deirdre O'Neill (2001), "What Is News? Galtung and Ruge revisited," *Journalism Studies*, 2 (2), 261–280.

Hardeck, Inga, J. William Harden, and David R. Upton (2019), "Consumer Reactions to Tax Avoidance: Evidence from the United States and Germany," *Journal of Business Ethics*, 170 (1), 75–96.

Hardeck, Inga and Rebecca Hertl (2014), "Consumer Reactions to Corporate Tax Strategies: Effects on Corporate Reputation and Purchasing Behavior," *Journal of Business Ethics*, 123 (2), 309–326.

Harrison, Jeffrey S., Robert A. Phillips, and R. Edward Freeman (2020), "On the 2019 Business Roundtable "Statement on the Purpose of a Corporation"," *Journal of Management*, 46 (7), 1223–1237.

Hart, Oliver and Luigi Zingales (2017), "Companies Should Maximize Shareholder Welfare Not Market Value," *Journal of Law, Finance, and Accounting*, 2 (2), 247–274.

Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80 (3), 1–24.

Hillman, Amy J. and Gerald D. Keim (2001), "Shareholder Value, Stakeholder Management, and Social Issues: What's the Bottom Line?," *Strategic Management Journal*, 22 (2), 125–139.

Hirsch, Barry T. and Terry G. Seaks (1993), "Functional Form in Regression Models of Tobin's q," *The Review of Economics and Statistics*, 75 (2), 381.

Hoi, Chun Keung, Qiang Wu, and Hao Zhang (2013), "Is Corporate Social Responsibility (CSR) Associated with Tax Avoidance? Evidence from Irresponsible CSR Activities," *The Accounting Review*, 88 (6), 2025–2059.

Holthausen, Robert W. and Robert E. Verrecchia (1990), "The Effect of Informedness and Consensus on Price and Volume Behavior," *Accounting Review*, 65 (1), 191–208.

Hope, Ole-Kristian, Yi Li, Qiliang Liu, and Han Wu (2021), "Newspaper Censorship in China: Evidence from Tunneling Scandals," *Management Science*, 67 (11), 7142–7166.

Hsu, Liwu and Benjamin Lawrence (2016), "The role of social media and brand equity during a product recall crisis: A shareholder value perspective," *International Journal of Research in Marketing*, 33 (1), 59–77.

ICIJ "Luxembourg Leaks: Global Companies' Secrets Exposed," (2014) https://www.icij.org/investigations/luxembourg-leaks/, (accessed April 11, 2023).

ICIJ "Paradise Papers: Secrets of the Global Elite," (2017) https://www.icij.org/investigations/paradise-papers/, (accessed April 11, 2023).

Interbrand "Best Global Brands," (2022) https://interbrand.com/best-brands/, (accessed April 11, 2023).

IR Magazine "Global Investor Relations Practice Report 2021," (2021) https://www.irmagazine.com/case-studies/global-investor-relations-practice-report-2021-available-now, (accessed April 11, 2023).

Jayachandran, Satish, Kartik Kalaignanam, and Meike Eilert (2013), "Product and environmental social performance: Varying effect on firm performance: Research Notes and Commentaries," *Strategic Management Journal*, 34 (10), 1255–1264.

Jeon, Yoontae, Thomas H. McCurdy, and Xiaofei Zhao (2022), "News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies," *Journal of Financial Economics*, 145 (2), 1–17.

Johansson, Johny K., Claudiu V. Dimofte, and Sanal K. Mazvancheryl (2012), "The performance of global brands in the 2008 financial crisis: A test of two brand value measures," *International Journal of Research in Marketing*, 29 (3), 235–245.

Kang, Charles, Frank Germann, and Rajdeep Grewal (2016), "Washing Away Your Sins? Corporate Social Responsibility, Corporate Social Irresponsibility, and Firm Performance," *Journal of Marketing*, 80 (2), 59–79.

Kang, Jingoo and Andy Y. Han Kim (2017), "The Relationship Between CEO Media Appearances and Compensation," *Organization Science*, 28 (3), 379–394.

Karlsen, Rune and Toril Aalberg (2021), "Social Media and Trust in News: An Experimental Study of the Effect of Facebook on News Story Credibility," *Digital Journalism*, pages 1–17.

Keller, Kevin L. (1993), "Conceptualizing, measuring, and managing customer-based brand equity," *Journal of Marketing*, 57, 1–22.

Kim, Oliver and Robert E. Verrecchia (1991), "Trading Volume and Price Reactions to Public Announcements," *Journal of Accounting Research*, 29 (2), 302–321.

Kim, Yongtae, Myung Seok Park, and Benson Wier (2012), "Is Earnings Quality Associated with Corporate Social Responsibility?," *The Accounting Review*, 87 (3), 761–796.

Kotchen, Matthew and Jon J. Moon (2012), "Corporate Social Responsibility for Irresponsibility," *The B.E. Journal of Economic Analysis & Policy*, 12 (1).

Kovach, Bill and Tom Rosenstiel (2021), *The Elements of Journalism: What Newspeople Should Know and the Public Should Expect* USA: Crown, 4th updated and revised edition.

Kölbel, Julian F., Timo Busch, and Leonhardt M. Jancso (2017), "How Media Coverage of Corporate Social Irresponsibility Increases Financial Risk," *Strategic Management Journal*, 38 (11), 2266–2284.

Lanis, Roman and Grant Richardson (2012), "Corporate social responsibility and tax aggressiveness: An empirical analysis," *Journal of Accounting and Public Policy*, 31 (1), 86–108.

Larcinese, Valentino, Riccardo Puglisi, and James M. Snyder (2011), "Partisan bias in economic news: Evidence on the agenda-setting behavior of U.S. newspapers," *Journal of Public Economics*, 95 (9), 1178–1189.

Leonhardt, David (2021), "The Amazon Customers Don't See," *The New York Times* https://www.nytimes.com/2021/06/15/briefing/amazon-warehouse-investigation.html, (accessed April 11, 2023).

Liu, Yan and Venkatesh Shankar (2015), "The Dynamic Impact of Product-Harm Crises on Brand Preference and Advertising Effectiveness: An Empirical Analysis of the Automobile Industry," *Management Science*, 61 (10), 2514–2535.

Luo, Xueming, Sascha Raithel, and Michael A. Wiles (2013), "The Impact of Brand Rating Dispersion on Firm Value," *Journal of Marketing Research*, 50 (3), 399–415.

Mafael, Alexander, Sascha Raithel, and Stefan J. Hock (2022), "Managing customer satisfaction after a product recall: the joint role of remedy, brand equity, and severity," *Journal of the Academy of Marketing Science*, 50 (1), 174–194.

Margolis, Joshua D., Hillary Anger Elfenbein, and James P. Walsh (2009), "Does it Pay to Be Good...And Does it Matter? A Meta-Analysis of the Relationship between Corporate Social and Financial Performance," *SSRN Electronic Journal*.

Markowitz, Harry (1952), "Portfolio Selection," *The Journal of Finance*, 7 (1), 77–91.

Mattingly, James E. and Shawn L. Berman (2006), "Measurement of Corporate Social Action: Discovering Taxonomy in the Kinder Lydenburg Domini Ratings Data," *Business & Society*, 45 (1), 20–46.

Mayberry, Michael A. and Luke Watson (2021), "Is Corporate Social Responsibility Related to Corporate Tax Avoidance? Evidence from a Natural Experiment," *Journal of the American Taxation Association*, 43 (1), 79–106.

McAlister, Leigh, Raji Srinivasan, and MinChung Kim (2007), "Advertising, Research and Development, and Systematic Risk of the Firm," *Journal of Marketing*, 71 (1), 35–48.

McGuire, Jean B., Alison Sundgren, and Thomas Schneeweis (1988), "Corporate Social Responsibility and Firm Financial Performance," *The Academy of Management Journal*, 31 (4), 854–872.

McInnes, Leland, John Healy, and Steve Astels "The hdbscan Clustering Library — hdbscan v0.8.1 documentation," (2016) https://hdbscan.readthedocs.io/en/latest/index.html, (accessed April 11, 2023).

McInnes, Leland, John Healy, and Steve Astels (2017), "hdbscan: Hierarchical density based clustering," *The Journal of Open Source Software*, 2 (11), 205.

McInnes, Leland, John Healy, and James Melville (2020), "UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction," *arXiv:1802.03426 [stat.ML]* https://arxiv.org/abs/1802.03426, (accessed April 11, 2023).

Meier, Stephan and Lea Cassar (2018), "Stop Talking About How CSR Helps Your Bottom Line," *Harvard Business Review* https://hbr.org/2018/01/stop-talking-about-how-csr-helps-your-bottom-line, (accessed April 11, 2023).

Mishra, Saurabh and Sachin B. Modi (2016), "Corporate Social Responsibility and Shareholder Wealth: The Role of Marketing Capability," *Journal of Marketing*, 80 (1), 26–46.

Mizik, Natalie (2010), "The Theory and Practice of Myopic Management," *Journal of Marketing Research*, 47 (4), 594–611.

Mizik, Natalie and Robert Jacobson "Stock Return Response Modeling," Christine Moorman and Donald R. Lehmann, editors, "Assessing Marketing Strategy Performance," pages 29–46, Cambridge: MA: Marketing Science Institute (2004).

Mizik, Natalie and Robert Jacobson (2008), "The Financial Value Impact of Perceptual Brand Attributes," *Journal of Marketing Research*, 45 (1), 15–32.

Moser, Donald V. and Patrick R. Martin (2012), "A Broader Perspective on Corporate Social Responsibility Research in Accounting," *The Accounting Review*, 87 (3), 797–806.

Nam, Hyoryung and P. K. Kannan (2014), "The Informational Value of Social Tagging Networks," *Journal of Marketing*, 78 (4), 21–40.

Neate, Rupert (2019), "Starbucks pays £18.3m tax but £348m in dividends," *The Guardian* https://www.theguardian.com/business/2019/jun/27/starbucks%2Demea%2Dpays-183m-tax-but-348m-in-royalty-payments, (accessed April 11, 2023).

Newmyer, Tory (2020), "The Finance 202: Elizabeth Warren charges CEOs with fixating on profits despite do-gooder pledge," *Washington Post* https://www.washingtonpost.com/politics/2020/09/18/finance-202-elizabeth%2Dwarren%2Dcharges-ceos-with-fixating-profits-despite-do-gooder-pledge/, (accessed April 11, 2023).

Nickerson, Dionne, Michael Lowe, Adithya Pattabhiramaiah, and Alina Sorescu (2022), "The Impact of Corporate Social Responsibility on Brand Sales: An Accountability Perspective," *Journal of Marketing*, 86 (2), 5–28.

Nikolaeva, Ralitza and Marta Bicha (2011), "The role of institutional and reputational factors in the voluntary adoption of corporate social responsibility reporting standards," *Journal of the Academy of Marketing Science*, 39 (1), 136–157.

OECD "130 countries and jurisdictions join bold new framework for international tax reform," (2021) https://www.oecd.org/newsroom/130-countries-and-jurisdictions-join-bold-new-framework-for-international-tax-reform.htm, (accessed April 11, 2023).

Orlitzky, Marc, Frank L. Schmidt, and Sara L. Rynes (2003), "Corporate Social and Financial Performance: A Meta-Analysis," *Organization Studies*, 24 (3), 403–441.

Pfarrer, Michael D., Timothy G. Pollock, and Violina P. Rindova (2010), "A Tale of Two Assets: The Effects of Firm Reputation and Celebrity on Earnings Surprises and Investors' Reactions," *Academy of Management Journal*, 53 (5), 1131–1152.

Rajaraman, Anand and Jeffrey David Ullman (2011), *Mining of Massive Datasets* Cambridge: Cambridge University Press, 3rd edition.

Rees, Lynn and Brady J. Twedt (2022), "Political Bias in the Media's Coverage of Firms' Earnings Announcements," *Accounting Review*, 97 (1), 389–411.

Reimers, Nils "SBERT Sentence-Transformers documentation - Pretrained Models," (2022) https://www.sbert.net/docs/pretrained_models.html, (accessed April 11, 2023).

Reimers, Nils and Iryna Gurevych (2019), "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks," *arXiv:1908.10084 [cs.CL]* https://arxiv.org/abs/1908.10084, (accessed April 11, 2023).

Rindova, Violina P., Antoaneta P. Petkova, and Suresh Kotha (2007), "Standing out: how new firms in emerging markets build reputation," *Strategic Organization*, 5 (1), 31–70.

Rust, Roland T., William Rand, Ming-Hui Huang, Andrew T. Stephen, Gillian Brooks, and Timur Chabuk (2021), "Real-Time Brand Reputation Tracking Using Social Media," *Journal of Marketing*, 85 (4), 21–43.

Salton, Gerard and Christopher Buckley (1988), "Term-weighting approaches in automatic text retrieval," *Information Processing & Management*, 24 (5), 513–523.

Schoen, John W. (2014), "Corporate taxes: Do companies pay their 'fair share' of taxes? Depends who you ask," *CNBC* https://cnb.cx/383WtJV, (accessed April 11, 2023).

Sen, Sankar and C.B. Bhattacharya (2001), "Does Doing Good Always Lead to Doing Better? Consumer Reactions to Corporate Social Responsibility," *Journal of Marketing Research*, 38 (2), 225–243.

Servaes, Henri and Ane Tamayo (2013), "The Impact of Corporate Social Responsibility on Firm Value: The Role of Customer Awareness," *Management Science*, 59 (5), 1045–1061.

Sharpe, William F. (1964), "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *The Journal of Finance*, 19 (3), 425.

Solomon, David H., Eugene Soltes, and Denis Sosyura (2014), "Winners in the spotlight: Media coverage of fund holdings as a driver of flows," *Journal of Financial Economics*, 113 (1), 53–72 https://www.sciencedirect.com/science/article/pii/S0304405X14000403, (accessed April 11, 2023).

Sorescu, Alina B. and Jelena Spanjol (2008), "Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods," *Journal of Marketing*, 72 (2), 114–132.

Sorkin, Andrew Ross (2020), "A Free Market Manifesto That Changed the World, Reconsidered," *The New York Times* https://www.nytimes.com/2020/09/11/business/dealbook/milton-friedman-doctrine-social-responsibility-of-business.html, (accessed April 11, 2023).

Srinivasan, Shuba and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46 (3), 293–312.

Srinivasan, Shuba, Koen Pauwels, Jorge Silva-Risso, and Dominique M. Hanssens (2009), "Product Innovations, Advertising, and Stock Returns," *Journal of Marketing*, 73 (1), 24–43.

Stiglitz, Joseph E. (2015), *Rewriting the Rules of the American Economy: An Agenda for Growth and Shared Prosperity* New York: W. W. Norton & Company, 1st edition.

Stout, Lynn A. (2013), "The Toxic Side Effects of Shareholder Primacy," *University of Pennsylvania Law Review*, 161 (7), 2003–2023.

Strike, Vanessa M., Jijun Gao, and Pratima Bansal (2006), "Being Good While Being Bad: Social Responsibility and the International Diversification of US Firms," *Journal of International Business Studies*, 37 (6), 850–862.

Stäbler, Samuel and Marc Fischer (2020), "When Does Corporate Social Irresponsibility Become News? Evidence from More Than 1,000 Brand Transgressions Across Five Countries," *Journal of Marketing*, 84 (3), 46–66.

Tax Justice Network "The State of Tax Justice 2021," (2021) https://taxjustice.net/reports/the-state-of-tax-justice-2021/, (accessed April 11, 2023).

Tetlock, Paul C. (2011), "All the News That's Fit to Reprint: Do Investors React to Stale Information?," *The Review of Financial Studies*, 24 (5), 1481–1512.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy (2008), "More Than Words: Quantifying Language to Measure Firms' Fundamentals," *The Journal of Finance*, 63 (3), 1437–1467.

Thomas, Anu and S. Sangeetha (2019), "An innovative hybrid approach for extracting named entities from unstructured text data," *Computational Intelligence*, 35 (4), 799–826.

Thompson, Jennifer and Vanessa Houlder (2012), "Starbucks faces boycott calls over tax affairs," *Financial Times* https://on.ft.com/U5NSMN, (accessed April 11, 2023).

Tuli, Kapil R. and Sundar G. Bharadwaj (2009), "Customer Satisfaction and Stock Returns Risk," *Journal of Marketing*, 73 (6), 184–197.

van der Maaten, Laurens and Geoffrey Hinton (2008), "Visualizing Data using t-SNE," *Journal of Machine Learning Research*, 9, 2579–2605.

Van Heerde, Harald J., Els Gijsbrechts, and Koen Pauwels (2015), "Fanning the Flames? How Media Coverage of a Price War Affects Retailers, Consumers, and Investors," *Journal of Marketing Research*, 52 (5), 674–693.

Wagner, Franz W. (2018), "Steuervermeidung und Corporate social responsibility," *Perspektiven der Wirtschaftspolitik*, 19 (1), 2–21.

Wang, Yang and Alexander Chaudhry (2018), "When and How Managers' Responses to Online Reviews Affect Subsequent Reviews," *Journal of Marketing Research (JMR)*, 55 (2), 163–177.

A

Appendix Chapter 2

A.1 Stock return response model sample splits

- *B2C focus*: Subsample of firms that are predominantly active in a business-to-consumer context
- *Low inst. own.*: Firms with a below-median average share of institutional ownership in the observation period (median: 88.4 %)
- *Tax issue*: Subsample of firms that have been mentioned in public tax disclosures
- *LuxLeaks*: Firms between Oct. 2014 and Feb. 2015 that were mentioned in the LuxLeaks
- *Paradise Papers*: Firms between Oct. 2017 and Feb. 2018 that were mentioned in the Paradise Papers

Table A.1: Stock return response model (results for different subsamples)

		Dependent Variable: Abnormal returns				
		B2C focus	Low inst. own.	Tax issue	LuxLeaks	Paradise Papers
$log(ArticleVol+1)$	β_1	0.0001 (0.0002)	0.0002 (0.0002)	0.0005 (0.0003)*	-0.0005 (0.0022)	0.0008 (0.0016)
$ArticleNeg$	γ_1	-0.0058 (0.0085)	0.0029 (0.0072)	0.0069 (0.0113)	0.0186 (0.0713)	-0.0139 (0.0644)
$log(TweetVol+1)$	β_2	0.0000 (0.0001)	0.0000 (0.0000)	-0.0000 (0.0001)	0.0006 (0.0006)	-0.0009 (0.0006)
$TweetNeg$	γ_2	-0.0004 (0.0005)	0.0003 (0.0004)	-0.0004 (0.0008)	-0.0055 (0.0048)	-0.0009 (0.0047)
$log(ArticleVol+1)*ArticleNeg$	ζ_1	-0.0026 (0.0147)	-0.0182 (0.0144)	-0.0357 (0.0210)*	-0.0356 (0.0659)	-0.0391 (0.1027)
$log(TweetVol+1)*TweetNeg$	ζ_2	0.0002 (0.0002)	-0.0002 (0.0002)	0.0003 (0.0004)	0.0018 (0.0018)	0.0050 (0.0019)**
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)	-0.0004 (0.0002)*	-0.0002 (0.0004)	0.0035 (0.0037)	-0.0107 (0.0244)
$log(ArticleVol+1)*U\Delta CashETR$	ρ_1	-0.0020 (0.0015)	-0.0004 (0.0014)	-0.0015 (0.0020)	-0.0252 (0.0218)	-0.0032 (0.0094)
$ArticleNeg*U\Delta CashETR$	θ_1	0.0317 (0.0562)	0.0002 (0.0502)	0.0533 (0.0695)	0.9764 (0.8053)	0.1226 (0.2866)
$log(TweetVol+1)*U\Delta CashETR$	ρ_2	0.0005 (0.0002)**	0.0002 (0.0002)	0.0003 (0.0003)	-0.0004 (0.0043)	0.0023 (0.0034)
$TweetNeg*U\Delta CashETR$	θ_2	0.0001 (0.0030)	-0.0010 (0.0023)	0.0005 (0.0044)	-0.0341 (0.0265)	0.0341 (0.0294)
$U\Delta ROA$	δ_1	0.0000 (0.0000)**	0.0001 (0.0000)**	0.0001 (0.0000)**	0.0004 (0.0005)	0.0015 (0.0006)**
$SalesGrowth$	δ_2	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0001)	-0.0014 (0.0011)	-0.0028 (0.0054)
$afterHoliday=True$	δ_3	0.0003 (0.0002)	0.0001 (0.0002)	0.0001 (0.0003)	0.0049 (0.0021)**	0.0005 (0.0023)
N		542,321	496,237	114,823	1,676	921
Adj. R^2		0.031	0.040	0.038	0.000	-0.008
Firm, weekday, and year FEs		yes	yes	yes	yes	yes

* p < .1, ** p < .05, *** p < .01

A.2 Definition of consumer brand metric variables

In this section, we give some additional information on the operationalization of the variables brand attention and brand strengths. Both variables are measured based on daily surveys conducted by the market research company YouGov. Consistent with prior studies (e.g., Hewett et al., 2016), we aggregate daily brand ratings to weekly ratings that are based on a large sample of approximately 500 randomly drawn responses, which helps reduce sampling error. Brand strength is measured based on the YouGov BrandIndex dimensions perceived quality, perceived value, consumer satisfaction, reputation, general impression, and recommendation. Additionally, YouGov also asks respondents with respect to a seventh item, which is called brand attention. The tables below provide details on the exact question for each item. Prior research (e.g., Luo, Raithel, and Wiles, 2013) has shown that these items pass all tests on item reliability and construct validity. Brand strength is a is a multidimensional index that runs from -100 to $+100$. Brand attention is measured on the basis of one dimension and indicates whether people have recently heard either nothing or something positive or / and negative about a brand and thus ranges from 0 to 100. We follow prior research (e.g., Backhaus and Fischer, 2016; Hanssens, Parsons, and Schultz, 2001) and rearrange the measurement of the consumer metrics as. $CM_{b,w}$ measures the consumer metric (brand strengths, alternatively brand attention) of brand b in week w. The function $f(\boldsymbol{X}_{b,w})$ captures the influence of corporate tax avoidance and controls, summarized in vector X. MAX and MIN indicate previous range restrictions (e.g., -100 to $+100$). Taking the logarithm and rearranging terms, the relation between our independent variables and brand strengths (alternatively, brand attention) follows an S-shape, satisfying the assumption of a normally distributed error term.

Logit Transformation (Step 1):

$$CM_{b,w} = MIN + (MAX - MIN)\frac{1}{1 + e^{-f(\boldsymbol{X}_{b,w})}} \tag{A.1}$$

Logit Transformation (Step 2):

$$\widetilde{CM}_{b,w} = ln(\frac{(CM_{b,w} - MIN)}{MAX - CM_{b,w})} = f(\boldsymbol{X}_{b,w}) \tag{A.2}$$

Table A.2: YouGov dimensions

Dimension	Positive question	Negative question
Impression	Overall, for which of the following brands do you have a positive impression?	Now for which of the following brands do you have an overall negative impression?
Quality	Which of the following brands do you think represents good quality?	Now which of the following brands represents poor quality?
Value	Which of the following brands do you think represents good value for money? By that we don't mean "cheap", but that the brands offer a customer a lot in return for the price paid.	Now which of the following brands do you think represents poor value for money? By that, we don't mean "expensive", but that the brands do not offer a customer much in return for the price paid .
Reputation	Imagine you were looking for a job (or advising a friend looking for a job). Which of the following brands would you be proud to work for. Imagine you (or your friend) were applying for the same sort of role at the following brands that you currently have or would apply for.	Now which of the following brands would you be embarrassed to work for? Imagine you (or your friend) were applying for the same sort of role at the following brands that you currently have or would apply for.
Satisfaction	For which of the following brands would you say that you are a "satisfied customer"?	For which of the following brands would you say that you are a "dissatisfied customer"?
Recommendation	Which of the following brands would you recommend to a friend or colleague?	And which of the following brands would you tell a friend or colleague to avoid?
Brand Attention	About which of the following brands have you recently heard anything positive either through media news, advertising, or word-of-mouth?	About which of the following brands have you recently heard anything negative either through media news, advertising, or word-of-mouth?

Notes: YouGov collects the data as follows. First, respondents select all brands for a given industry sector for which they agree to either a positive question or a negative question. All other brands are rated as neutral. Thus, in line with established research on attitudinal scales (Bearden, Netemeyer, and Haws, 2011), a brand is rated positively, neutrally, or negatively. The final brand strength metric is then transformed to an index ranging from -100 to +100.

A.3 Stock return response model robustness checks

Table A.3: Stock return response model (no imputation of missing cash ETRs)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	0.0002 (0.0002)	0.0002 (0.0002)	
$ArticleNeg$	γ_1	0.0068 (0.0077)	0.0064 (0.0077)	
$log(TweetVol + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg$	γ_2	0.0002 (0.0003)		0.0002 (0.0003)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.0212 (0.0141)	-0.0204 (0.0139)	
$log(TweetVol + 1) * TweetNeg$	ζ_2	0.0000 (0.0002)		-0.0000 (0.0002)
$U\Delta CashETR(NA)$	ϕ	-0.0003 (0.0002)*	-0.0003 (0.0002)*	-0.0003 (0.0002)*
$log(ArticleVol + 1) * U\Delta CashETR(NA)$	ρ_1	-0.0013 (0.0012)	-0.0011 (0.0012)	
$ArticleNeg * U\Delta CashETR(NA)$	θ_1	0.0140 (0.0445)	0.0141 (0.0443)	
$log(TweetVol + 1) * U\Delta CashETR(NA)$	ρ_2	0.0002 (0.0002)		0.0001 (0.0002)
$TweetNeg * U\Delta CashETR(NA)$	θ_2	0.0010 (0.0022)		0.0011 (0.0022)
$U\Delta ROA$	δ_1	0.0000 (0.0000)***	0.0000 (0.0000)***	0.0000 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0001)*	-0.0001 (0.0001)*	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0004 (0.0002)*	0.0004 (0.0002)*	0.0004 (0.0002)**
N		879,136	879,136	879,136
Adj. R^2		0.036	0.036	0.036
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

Table A.4: Stock return response model (missing negativities imputed with firm mean)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol+1)$	β_1	-0.0001 (0.0001)	-0.0000 (0.0001)	
$ArticleNeg(fm)$	γ_1	0.0092 (0.0179)	0.0111 (0.0177)	
$log(TweetVol+1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg(fm)$	γ_2	0.0001 (0.0005)		-0.0001 (0.0005)
$log(ArticleVol+1)*ArticleNeg(fm)$	ζ_1	-0.0270 (0.0242)	-0.0285 (0.0236)	
$log(TweetVol+1)*TweetNeg(fm)$	ζ_2	0.0000 (0.0002)		0.0001 (0.0002)
$U\Delta CashETR$	ϕ	-0.0004 (0.0002)*	-0.0003 (0.0002)	-0.0002 (0.0002)
$log(ArticleVol+1)*U\Delta CashETR$	ρ_1	-0.0006 (0.0007)	-0.0003 (0.0006)	
$ArticleNeg(fm)*U\Delta CashETR$	θ_1	0.0357 (0.0378)	0.0212 (0.0371)	
$log(TweetVol+1)*U\Delta CashETR$	ρ_2	0.0003 (0.0002)*		0.0002 (0.0002)
$TweetNeg(fm)*U\Delta CashETR$	θ_2	0.0001 (0.0028)		-0.0020 (0.0024)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0000 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0000)	-0.0001 (0.0000)	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0002 (0.0002)	0.0002 (0.0002)	0.0003 (0.0002)
N		525,509	538,421	909,339
Adj. R^2		0.035	0.035	0.033
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

Table A.5: Stock return response model (no interactions)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	0.0001 (0.0001)	0.0001 (0.0001)	
$ArticleNeg$	γ_1	-0.0068 (0.0051)	-0.0067 (0.0051)	
$log(TweetVol + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg$	γ_2	0.0002 (0.0003)		0.0002 (0.0003)
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)**	-0.0003 (0.0002)**	-0.0003 (0.0002
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0001 (0.0000)
$SalesGrowth$	δ_2	-0.0001 (0.0001)*	-0.0001 (0.0001)*	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0003 (0.0002)	0.0003 (0.0002)*	0.0003 (0.0002)
N		1,009,816	1,009,816	1,009,816
Adj. R^2		0.033	0.033	0.033
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

Table A.6: Stock return response model (3 day rolling sums (averages) for media attention)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol3day + 1)$	β_1	-0.0000 (0.0001)	-0.0000 (0.0001)	
$ArticleNeg3day$	γ_1	0.0065 (0.0101)	0.0064 (0.0101)	
$log(TweetVol3day + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg3day$	γ_2	0.0004 (0.0005)		0.0004 (0.0005)
$log(ArticleVol3day + 1) * ArticleNeg3day$	ζ_1	-0.0036 (0.0061)	-0.0031 (0.0060)	
$log(TweetVol3day + 1) * TweetNeg3day$	ζ_2	0.0000 (0.0002)		0.0000 (0.0002)
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)**	-0.0004 (0.0002)**	-0.0003 (0.0002)**
$log(ArticleVol3day + 1) * U\Delta CashETR$	ρ_1	-0.0007 (0.0009)	-0.0003 (0.0009)	
$ArticleNeg3day * U\Delta CashETR$	θ_1	0.0357 (0.0815)	0.0387 (0.0806)	
$log(TweetVol3day + 1) * U\Delta CashETR$	ρ_2	0.0004 (0.0002)**		0.0004 (0.0002)**
$TweetNeg3day * U\Delta CashETR$	θ_2	-0.0034 (0.0035)		-0.0033 (0.0035)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0001 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0001 (0.0001)
$afterHoliday = True$	δ_3	0.0003 (0.0002)	0.0003 (0.0002)	0.0003 (0.0002)
N		1,009,112	1,009,112	1,009,112
Adj. R^2		0.033	0.033	0.033
Firm, weekday, and year FEs		yes	yes	yes
* p < .1, ** p < .05, *** p < .01				

Table A.7: Stock return response model (realized returns as DV)

		Dependent Variable: Realized returns		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	0.0004 (0.0002)*	0.0005 (0.0002)*	
$ArticleNeg$	γ_1	0.0030 (0.0079)	0.0031 (0.0080)	
$log(TweetVol + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg$	γ_2	0.0000 (0.0004)		0.0001 (0.0004)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.0294 (0.0135)**	-0.0300 (0.0136)**	
$log(TweetVol + 1) * TweetNeg$	ζ_2	-0.0002 (0.0002)		-0.0003 (0.0002)
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)*	-0.0003 (0.0002)*	-0.0003 (0.0002)*
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	-0.0025 (0.0013)*	-0.0021 (0.0013)*	
$ArticleNeg * U\Delta CashETR$	θ_1	0.0619 (0.0506)	0.0613 (0.0503)	
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.0003 (0.0002)		0.0002 (0.0002)
$TweetNeg * U\Delta CashETR$	θ_2	0.0006 (0.0024)		0.0008 (0.0024)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0001 (0.0000)***
$SalesGrowth$	δ_2	0.0000 (0.0001)	0.0000 (0.0001)	0.0000 (0.0001)
$afterHoliday = True$	δ_3	0.0009 (0.0003)***	0.0009 (0.0003)***	0.0009 (0.0003)***
N		1,009,816	1,009,816	1,009,816
Adj. R^2		0.001	0.001	0.001
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

Table A.8: Stock return response model (reduced sample from trading volume models)

		Dependent Variable: Abnormal returns		
		Full model	Articles model	Tweets model
$log(ArticleVol + 1)$	β_1	0.0003 (0.0002)	0.0003 (0.0002)	
$ArticleNeg$	γ_1	0.0023 (0.0073)	0.0017 (0.0073)	
$log(TweetVol + 1)$	β_2	0.0000 (0.0000)		0.0000 (0.0000)
$TweetNeg$	γ_2	0.0001 (0.0004)		0.0002 (0.0004)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	-0.0214 (0.0133)	-0.0205 (0.0132)	
$log(TweetVol + 1) * TweetNeg$	ζ_2	-0.0000 (0.0002)		-0.0000 (0.0002)
$U\Delta CashETR$	ϕ	-0.0004 (0.0002)**	-0.0004 (0.0002)**	-0.0004 (0.0002)**
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	-0.0015 (0.0013)	-0.0011 (0.0013)	
$ArticleNeg * U\Delta CashETR$	θ_1	0.0249 (0.0480)	0.0243 (0.0475)	
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.0003 (0.0002)		0.0002 (0.0002)
$TweetNeg * U\Delta CashETR$	θ_2	0.0004 (0.0022)		0.0006 (0.0022)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***	0.0001 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0001)*	-0.0001 (0.0001)*	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0003 (0.0002)	0.0003 (0.0002)	0.0003 (0.0002)
N		992,214	992,214	992,214
Adj. R^2		0.033	0.033	0.033
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

Table A.9: Stock return response model with time trend

		Dependent Variable: Abnormal returns	
		Full model	Full model * time
$log(ArticleVol+1)$	β_1	0.0003 (0.0002)	-0.0003 (0.0003)
$ArticleNeg$	γ_1	0.0037 (0.0073)	-0.0207 (0.0190)
$log(TweetVol+1)$	β_2	0.0000 (0.0000)	0.0000 (0.0001)
$TweetNeg$	γ_2	0.0002 (0.0004)	-0.0001 (0.0009)
$log(ArticleVol+1)*ArticleNeg$	ζ_1	-0.0209 (0.0134)	0.0158 (0.0317)
$log(TweetVol+1)*TweetNeg$	ζ_2	0.0000 (0.0002)	0.0001 (0.0004)
$U\Delta CashETR$	ϕ	-0.0003 (0.0002)**	-0.0002 (0.0002)
$log(ArticleVol+1)*U\Delta CashETR$	ρ_1	-0.0013 (0.0013)	-0.0013 (0.0013)
$ArticleNeg*U\Delta CashETR$	θ_1	0.0284 (0.0473)	0.0280 (0.0465)
$log(TweetVol+1)*U\Delta CashETR$	ρ_2	0.0003 (0.0002)	0.0003 (0.0002)
$TweetNeg*U\Delta CashETR$	θ_2	0.0001 (0.0022)	0.0002 (0.0022)
$U\Delta ROA$	δ_1	0.0001 (0.0000)***	0.0001 (0.0000)***
$SalesGrowth$	δ_2	-0.0001 (0.0001)*	-0.0001 (0.0001)*
$afterHoliday = True$	δ_3	0.0003 (0.0002)	0.0003 (0.0002)
$log(ArticleVol+1)*Year$	δ_4		0.0001 (0.0001)*
$ArticleNeg*Year$	δ_5		0.0048 (0.0027)*
$log(TweetVol+1)*Year$	δ_6		-0.0000 (0.0000)
$TweetNeg*Year$	δ_7		0.0000 (0.0001)
$U\Delta CashETR*Year$	δ_8		-0.0000 (0.0000)
$log(ArticleVol+1)*ArticleNeg*Year$	δ_9		-0.0070 (0.0046)
$log(TweetVol+1)*TweetNeg*Year$	δ_{10}		-0.0000 (0.0001)
N		1,009,816	1,009,816
Adj. R^2		0.033	0.033
Firm, weekday, and year FEs		yes	yes

* p < .1, ** p < .05, *** p < .01

A.4 Tweet negativity ratings

On a scale from 0 (not negative at all) to 4 (extremely negative), how negatively do you perceive this tweet regarding the tax morale of the mentioned company?

Examples of tweets hand-labeled with a consensus rating of negativity = 4

- "Don't buy the new iPhone until Apple pays its taxes"
- "The real issue here is Amazon pays zero Tax. GE pays Zero Tax. WHo the hell pays the taxes ? The people. Fuck that shit. Many of us live paycheck to paycheck. Make corporations and CHURCHES pay their fair share ! #eattherich"

Examples of tweets hand-labeled with a consensus rating of negativity = 3

- "Petition via @4TaxFairness: Tell @McConnellPress to end General Electric's tax loophole"
- "Well, when you decide that rich ppl and corporations don't have to pay taxes, working people are all you have left. Trump voters are incredibly gullible. Read yesterday that AT&T has never stopped off-shoring call centers and laying off workers."

Examples of tweets hand-labeled with a consensus rating of negativity = 2

- "Interesting that corporation tax is cut to 20%. The likes of Amazon, Google & Starbucks must be grinning from ear to ear. Oh, wait."
- "Yeah drain the swamp...start with trump and all his Goldman Sachs buddy's that wrote the tax scam cuts for themselves. LoL"

Examples of tweets hand-labeled with a consensus rating of negativity = 1

- "#Tax rate for corporates in #Ireland is 12%. Can you blame companies like US domiciled @Pfizer wanting to relocate? Why pay 25-30 % or more?"
- "I'm not defending Amazon. It's our archaic tax system that allows them to do it. If it was you, you'd do the same."

Examples of tweets hand-labeled with a consensus rating of negativity = 0

- "GM have wanted to close Oshawa down for a very long time. The government bailout delayed the inevitable for 10 years. Canadian auto unions and the Liberal governments have made it far too expensive to build cars in Ontario. Look no further then Trudeau's brand new carbon tax."
- "yup, I got screwed, IRS, state taxes, credit card, paypal, etc "

Examples of tweets with the highest DNN-predictions for negativity (predicted scores in parenthesis)

- "@BernieUpstateNY You know who doesn't pay taxes? Corporations like GE who hold trillions in offshore tax havens to avoid paying their fair share, Fuck em." (0.7876)
- "http://t.co/oqdekvVd Microsoft avoids paying £159m in tax EVERY YEAR using Luxembourg tax loophole. Close the loophole = paid taxes." (0.7769)
- "boycott Amazon & Starbucks until they pay Tax! Don't think of sitting in Starbucks using their free wifi whilst ordering Jimmy Carr dvd!!" (0.7689)
- "Companies like General Electric, Boeing, and eBay paid more to their CEOs last year than they paid in US federal taxes: http://t.co/STkJVQE" (0.7599)
- "Boeing reported $9.7B in pretax US profits from 2008-10 - paid no taxes - and received $3.5B in tax rebates." (0.7598)

Examples of tweets with the lowest DNN-predictions for negativity (predicted scores in parenthesis)

- "Getting ready for Vegas vacation next week I went to Walmart and bought new shorts along with T shirts along with some food items. I finished my tax return on H&R Blocks free online for my puny refund withheld from my pension plan." (0.0001)
- "Cool Apple store now gives military same discount as Educational. Got my Magic Mouse tax free plus a couple bucks off." (0.0001)
- "Last weekend I went to Walmart on a Saturday. Today I'm at Best Buy on a tax free weekend. I need my head examined." (0.0002)
- "i have something that's $90 in my cart, linked my paypal and everything and then.... $7 shipping plus $6 tax... i cancelled it LMAO" (0.0002)
- "This thing called tax on @amazon makes me sad. I love my #prime but want my #taxfreedom back. Still beats going to #Walmart" (0.0002)

A.5 Sentiment dictionary

Following Chen, Schuchard, and Stomberg (2019).

ABUSE
ACCUSE
ADVANTAGE
AGGRESSION
AGGRESSIVE
ALLEGATION
ALLEGE
ANGER
ANGRY
ANTI-ABUSE
ARBITRAGE
ARCANA
ARCANE
ARGUE
ARRANGE
ARRANGEMENT
ARTIFICIAL
ARTISTRY
ASSAULT
ASSERTIVE
ATTACK
AVOID
BACK TAX
BACK TAXES
BAILOUT
BATTLE
BLOCK
BOGUS
BOYCOTT
BREAK
BURDEN
CHALLENGE
CHEAT
CIRCUMVENT
COMPLAIN
COMPLEX
COMPLICATE
CONCERN
CONFLICT
CONTROVERSE
CONTROVERSY
CONVOLUTED
CRACKDOWN
CRIMINAL
CRITIC
CURB
CURTAIL
CUT
DEAL
DEBATE
DEFEND
DEFER
DEFRAUD
DENOUNCE
DENUNCIATION
DISALLOW
DISAPPEAR
DISAPPOINT
DISCOUNT
DISGUISE
DISINGENUOUS
DISPUTE
DISTORT
DODGE
DODGING
DUBIOUS
EGREGIOUS
ELIMINATE
ENFORCE
ERODE
EROSION
ESCAPE
EVADE
EVASION
EVIL
EXEMPT
EXILE
EXOTIC
EXPLOIT
FAIR
FAIR SHARE
FIGHT
FLAK
FLEE
FORBID
FORCE
FRAUD
FUNNEL
FURIOUS
FUROR
GAME
GIMMICK
GIVEAWAY
GRANT
GUILT
HAVEN
HEARING
HIT
HOLIDAY
HORRIBLE
HURT
ILLEGAL
ILLEGITIMATE
IMMORAL
IMPROPER
INCORRECT
INEQUITY
INQUIRY
INVESTIGATE
INVESTIGATION
LACK
LAMENT
LAWSUIT
LITTLE
LOBBY
LOOPHOLE
LOSS
LOST
LOW TAX
LOWER
MANEUVER
MANIPULATE
MANIPULATION
MASK
MASSIVE
MINIMIZE
MISCONDUCT
MISLEAD
MURKY
NO TAX
OBJECTION
OBSCURE
OFFSHORE
OPPOSE
OPPOSING
OVERHAUL
PAPER TRANSACTION
PARADOX
PAY LITTLE
PAY LOW
PAY NO
PENALIZE
PENALTY
PHONY
PILE
PLANNING
PLOT
PLOY
POLICY
PRESSURE
PROBE
PROBLEM
PROHIBITED
PROP
PROSECUTE
PROSECUTOR
PUNY
QUESTIONABLE
REAP
REDUCE
REDUCTION
RESENTFUL
RESENTMENT
RICH
SANCTION
SAVE
SCANDAL
SCATHING
SCHEME
SCHEMES
SCRUTINISE
SCRUTINIZE
SCRUTINY
SECRECY
SECRET
SETTLEMENT
SETTLEMENTS
SHADOWY
SHAM
SHAVE
SHELL
SHELTER
SHIELD
SHIFT
SHOCK
SHUTTLE
SIDESTEP
SKEWED
SLASH
SO-CALLED
SPECIAL TREATMENT
SPECIAL-INTEREST
SPOTLIGHT
SPOTTY
STASH
STRATEGIC
STRATEGY
STRUCTURED
SUBSIDIES
SUBSIDISE
SUBSIDIZE
SUE
SWEETHEART
SYNERGISTIC
SYNERGY
TAKE ADVANTAGE
TARGET
TAX BENEFIT
TAX BENEFITS
TAX CREDIT
TAX CREDITS
TAX CUT
TAX DRIVEN
TAX FRIENDLY
TAX GIFT
TAX REFORM
TECHNIQUE
THREAT
THWARTED
TOUGH
TRANSACTION
TRANSACTIONS
TRAP
UNDER FIRE
UNEASE
UNFAIR
UNPRECEDENTED
WEAKNESS
WEAKNESSES
WHISTLEBLOWER
WIPE OUT
WITHHOLD
WITHHOLDING
WRITEOFF
WRONG
ZERO TAX

A.6 Fama-French-Carhart factors

Table A.10: Variable descriptions of Fama-French-Carhart factors

Variable	Notation	Description	Data source
Fama-French-Carhart factors			
Market risk premium	$Rm_t - Rf_t$	Market returns less risk-free rate of return on trading day t	Kenneth French's website
Small minus big	SMB_t	Outperformance of small versus big companies on trading day t	Kenneth French's website
High minus low	HML_t	Outperformance of high versus low book-to-market companies on trading day t	Kenneth French's website
Winners minus losers	WML_t	Outperformance of previous period winners versus losers on trading day t (aka "momentum")	Kenneth French's website

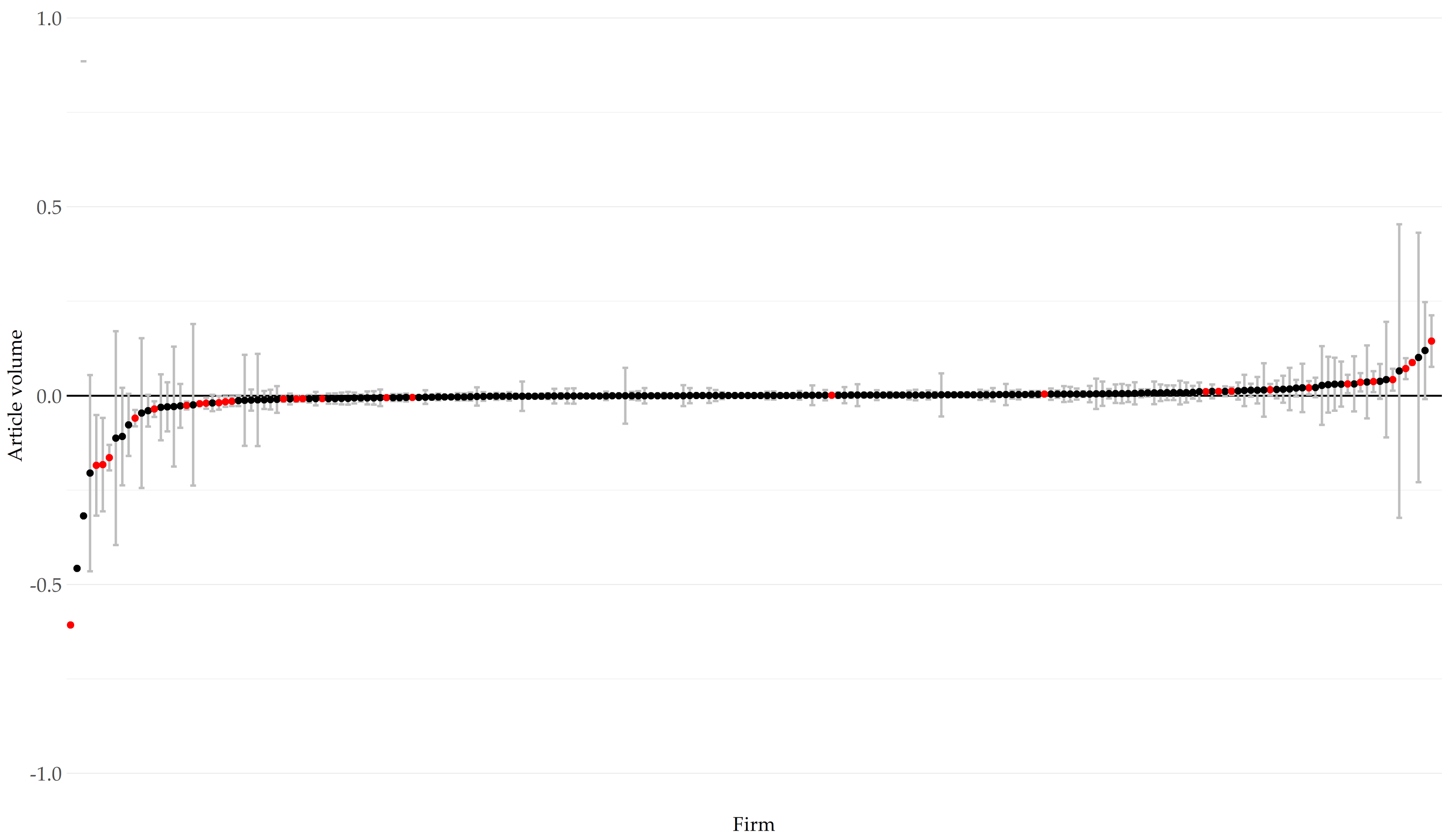
Table A.11: Descriptive statistics for Fama-French-Carhart factors

	N	Min.	$Q_{0.25}$	Median	Mean	$Q_{0.75}$	Max.	SD
Fama-French-Carhart factors								
$Rm_t - Rf_t$	2,598	-6.970	-0.360	0.080	0.059	0.558	6.890	1.064
Rf_t	2,598	-2.090	-0.330	0.010	0.003	0.340	3.600	0.544
SMB_t	2,598	-4.240	-0.330	-0.030	-0.008	0.290	4.340	0.618
HML_t	2,598	0.000	0.000	0.000	0.002	0.001	0.010	0.003
WML_t	2,598	-8.210	-0.390	0.045	-0.010	0.420	7.010	0.901

A.7 Unpooled firm-specific estimates of focal variables

Table A.12: Largest and smallest unpooled firm-specific estimates of article volume

	Company name	Ticker	Industry	n	Coef. *article_vol*	Sig.?
1	Corning	GLW	Electronics, Electrical Equip.	2591	-0.6071	Yes
2	United Continental Holdings	UAL	Airlines	2558	-0.4571	No
3	American Airlines Group	AAL	Airlines	1351	-0.3183	No
4	Avon Products	AVP	Household and Personal Products	2569	-0.2052	No
5	Laboratory Corp. of America	LH	Health Care: Pharmacy and Other Services	2596	-0.1843	Yes
6	Booz Allen Hamilton	BAH	Information Technology Services	1086	-0.1826	Yes
7	Danaher	DHR	Medical Products and Equipment	2597	-0.1639	Yes
8	Enterprise Products Partners	EPD	Pipelines	2595	-0.1127	No
9	Charter Communications	CHTR	Telecommunications	2362	-0.1083	No
10	Micron Technology	MU	Semiconductors and Other Electronic Components	2566	-0.0774	No
...	...	...	...	...	...	...
204	Freeport-McMoRan	FCX	Mining, Crude-Oil Production	2568	0.0378	No
205	Lincoln National	LNC	Insurance: Life, Health (stock)	2558	0.0422	Yes
206	Wynn Resorts	WYNN	Hotels, Casinos, Resorts	2570	0.0422	No
207	American Electric Power	AEP	Utilities: Gas and Electric	2597	0.0651	No
208	Entergy	ETR	Utilities: Gas and Electric	2598	0.0716	Yes
209	National Oilwell Varco	NOV	Oil and Gas Equipment, Services	2590	0.0876	Yes
210	Xcel Energy	XEL	Utilities: Gas and Electric	2598	0.1013	No
211	Envision Healthcare	EVHC	Health Care: Pharmacy and Other Services	2381	0.1193	No
212	Hartford Financial Services	HIG	Insurance: Property and Casualty (Stock)	2540	0.1444	Yes
213	JetBlue Airways	JBLU	Airlines	2582	4.243	Yes

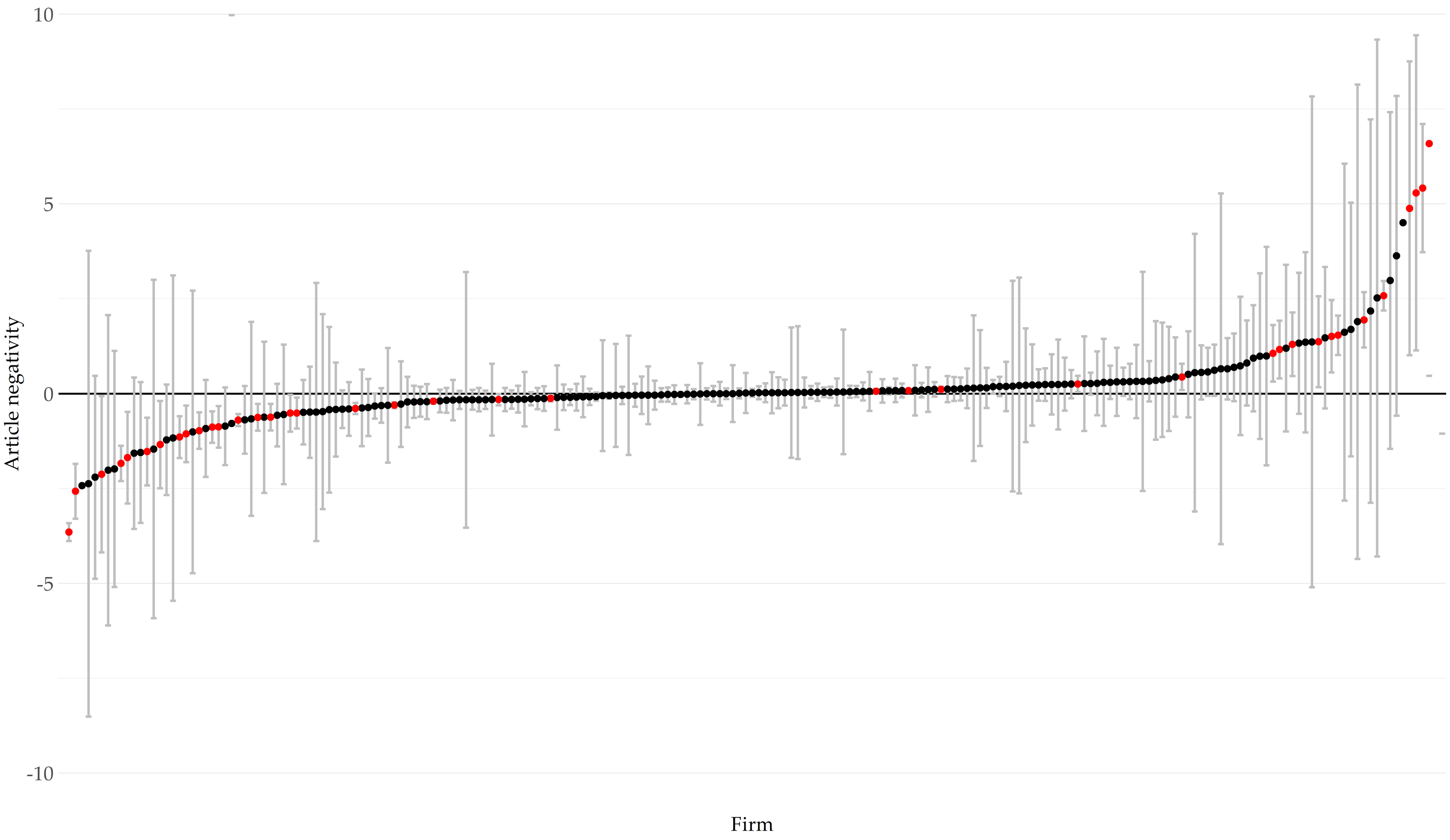


Unpooled firm-specific estimates of article volume with 95% confidence intervals sorted by effect size. Statistically significant coefficients printed in red. Effect sizes winsorized at [-1,1].

Figure A.1: Unpooled firm-specific estimates of article volume

Table A.13: Largest and smallest unpooled firm-specific estimates of article negativity

	Company name	Ticker	Industry	n	Coef. $article\_neg$	Sig.?
1	JetBlue Airways	JBLU	Airlines	2582	-267.9345	Yes
2	National Oilwell Varco	NOV	Oil and Gas Equipment, Services	2590	-3.649	Yes
3	Hartford Financial Services	HIG	Insurance: Property and Casualty (Stock)	2540	-2.5747	Yes
4	American Electric Power	AEP	Utilities: Gas and Electric	2597	-2.4257	No
5	Xcel Energy	XEL	Utilities: Gas and Electric	2598	-2.3739	No
6	Steel Dynamics	STLD	Metals	2579	-2.2054	No
7	NextEra Energy	NEE	Utilities: Gas and Electric	2598	-2.1258	Yes
8	Valero Energy	VLO	Petroleum Refining	2592	-2.0205	No
9	Coty	COTY	Household and Personal Products	767	-1.9875	No
10	Pioneer Natural Resources	PXD	Mining, Crude-Oil Production	2586	-1.8372	Yes
...	...	...	...	...	...	...
203	Ryder System	R	Trucking, Truck Leasing	2590	2.5193	No
204	Franklin Resources	BEN	Securities	2593	2.5802	Yes
205	Sempra Energy	SRE	Utilities: Gas and Electric	2597	2.9834	No
206	Micron Technology	MU	Semiconductors and Other Electronic Components	2566	3.6297	No
207	United Continental Holdings	UAL	Airlines	2558	4.5061	No
208	Laboratory Corp. of America	LH	Health Care: Pharmacy and Other Services	2596	4.884	Yes
209	Booz Allen Hamilton	BAH	Information Technology Services	1086	5.2923	Yes
210	Danaher	DHR	Medical Products and Equipment	2597	5.4149	Yes
211	Avon Products	AVP	Household and Personal Products	2569	6.5909	Yes
212	Corning	GLW	Electronics, Electrical Equip.	2591	21.3052	Yes
213	American Airlines Group	AAL	Airlines	1351	31.7847	No

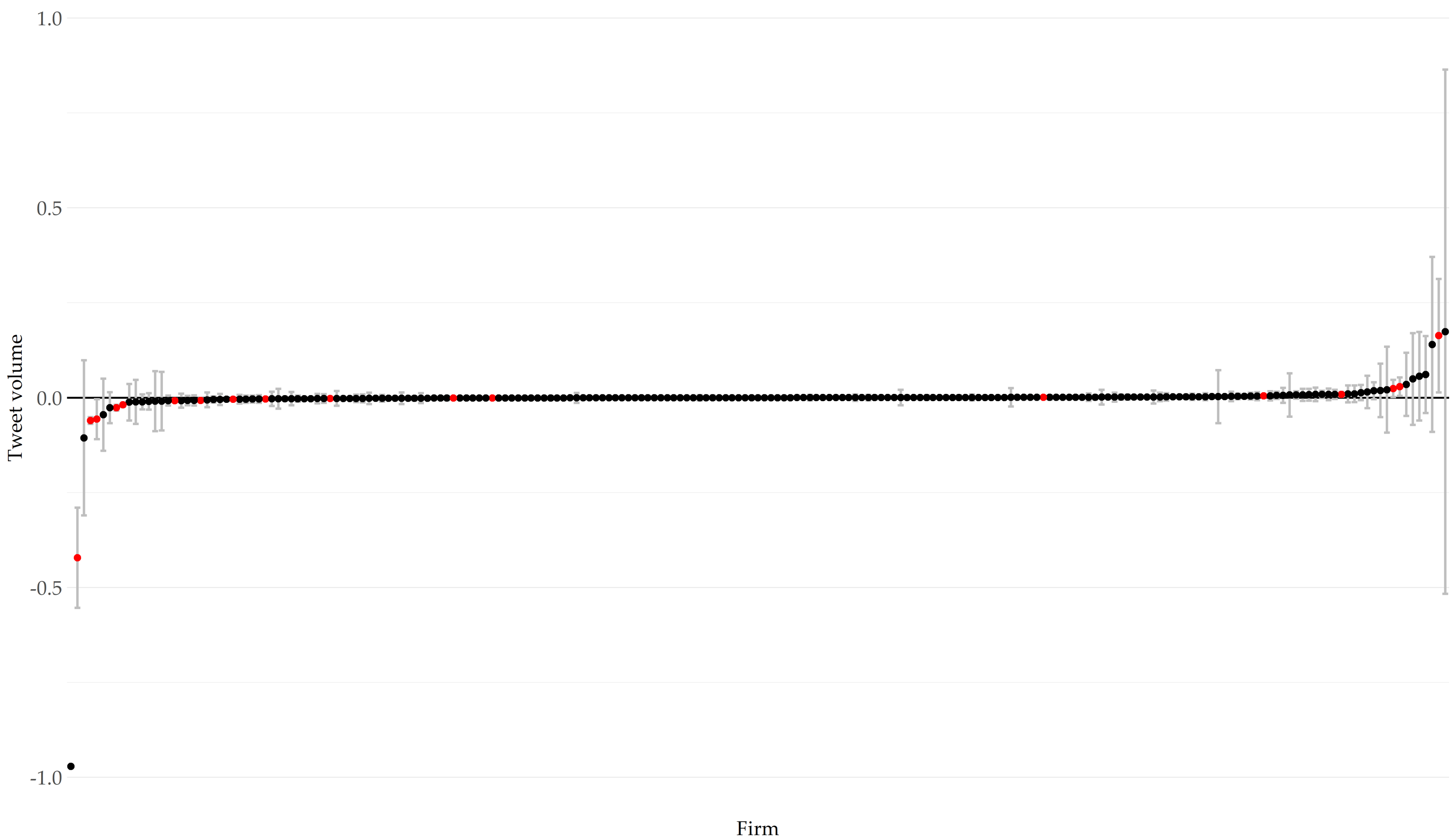


Unpooled firm-specific estimates of article negativity with 95% confidence intervals sorted by effect size. Statistically significant coefficients printed in red. Effect sizes winsorized at [-10,10].

Figure A.2: Unpooled firm-specific estimates of article negativity

Table A.14: Largest and smallest unpooled firm-specific estimates of tweet volume

	Company name	Ticker	Industry	n	Coef. $tweet\_vol$	Sig.?
1	National Oilwell Varco	NOV	Oil and Gas Equipment, Services	2590	-0.9714	No
2	Travelers Cos.	TRV	Insurance: Property and Casualty (Stock)	2598	-0.4219	Yes
3	Wynn Resorts	WYNN	Hotels, Casinos, Resorts	2570	-0.1058	No
4	Hilton Worldwide Holdings	HLT	Hotels, Casinos, Resorts	459	-0.0603	Yes
5	Avon Products	AVP	Household and Personal Products	2569	-0.0567	Yes
6	Las Vegas Sands	LVS	Hotels, Casinos, Resorts	2545	-0.0448	No
7	Ryder System	R	Trucking, Truck Leasing	2590	-0.0263	No
8	Intercontinental Exchange	ICE	Securities	2471	-0.0262	Yes
9	Owens-Illinois	OI	Packaging, Containers	2589	-0.0188	Yes
10	Freeport-McMoRan	FCX	Mining, Crude-Oil Production	2568	-0.012	No
...	...	...	...	...	...	...
204	Xcel Energy	XEL	Utilities: Gas and Electric	2598	0.0209	No
205	Micron Technology	MU	Semiconductors and Other Electronic Components	2566	0.0241	Yes
206	Magellan Health	MGLN	Health Care: Insurance and Managed Care	2585	0.0291	Yes
207	Charter Communications	CHTR	Telecommunications	2362	0.0349	No
208	Enterprise Products Partners	EPD	Pipelines	2595	0.0494	No
209	American Airlines Group	AAL	Airlines	1351	0.0564	No
210	Expedia Group	EXPE	Internet Services and Retailing	2519	0.061	No
211	Envision Healthcare	EVHC	Health Care: Pharmacy and Other Services	2381	0.1401	No
212	JetBlue Airways	JBLU	Airlines	2582	0.1633	Yes
213	United Continental Holdings	UAL	Airlines	2558	0.1737	No

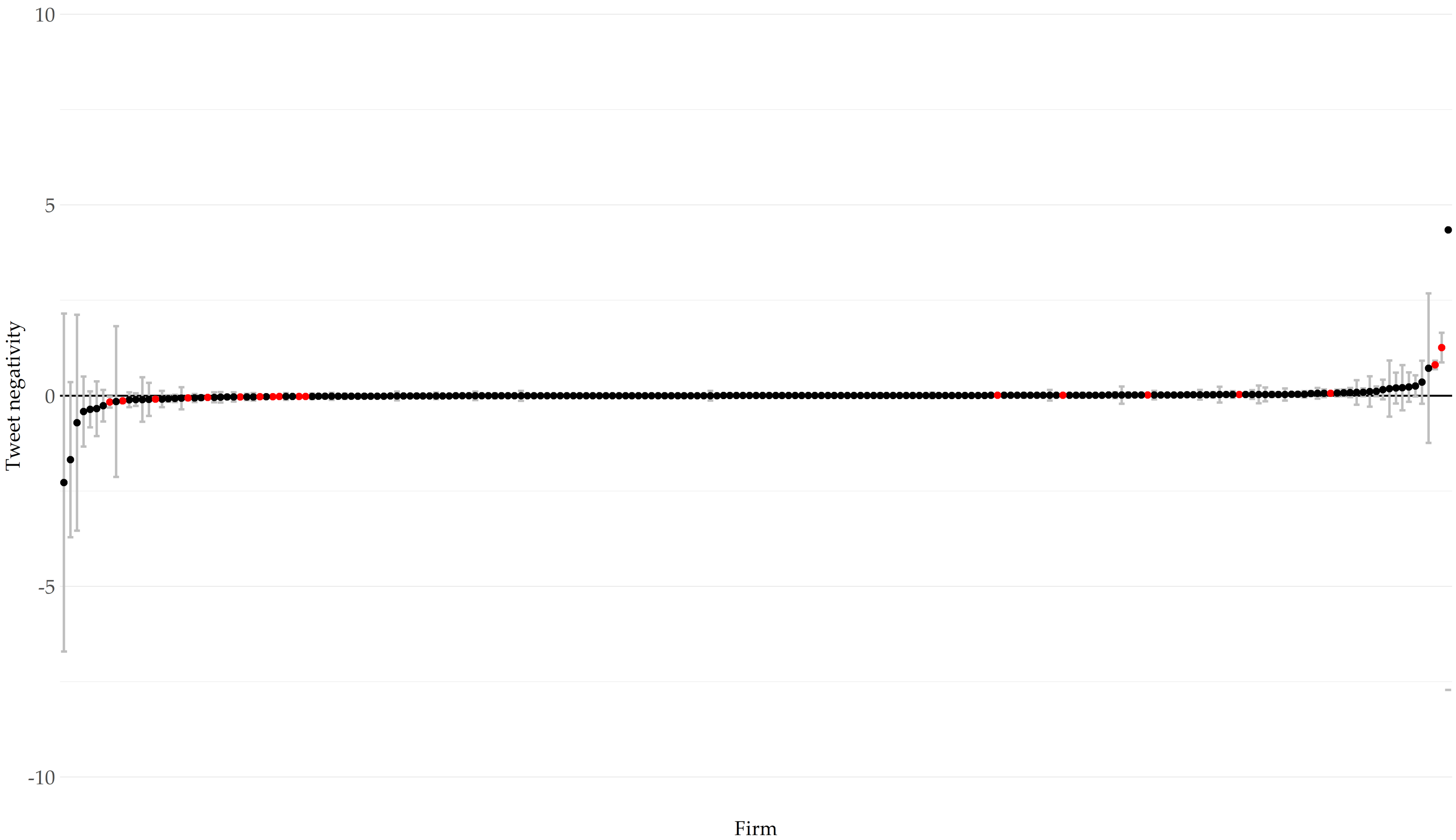


Unpooled firm-specific estimates of tweet volume with 95% confidence intervals sorted by effect size. Statistically significant coefficients printed in red. Effect sizes winsorized at [-1,1].

Figure A.3: Unpooled firm-specific estimates of tweet volume

Table A.15: Largest and smallest unpooled firm-specific estimates of tweet negativity

	Company name	Ticker	Industry	n	Coef. $tweet\_neg$	Sig.?
1	United Continental Holdings	UAL	Airlines	2558	-2.2791	No
2	JetBlue Airways	JBLU	Airlines	2582	-1.6778	No
3	American Airlines Group	AAL	Airlines	1351	-0.7103	No
4	Magellan Health	MGLN	Health Care: Insurance and Managed Care	2585	-0.4183	No
5	Charter Communications	CHTR	Telecommunications	2362	-0.3606	No
6	Envision Healthcare	EVHC	Health Care: Pharmacy and Other Services	2381	-0.3424	No
7	Expedia Group	EXPE	Internet Services and Retailing	2519	-0.2643	No
8	KKR	KKR	Securities	1215	-0.1701	Yes
9	Xcel Energy	XEL	Utilities: Gas and Electric	2598	-0.1558	No
10	Lincoln National	LNC	Insurance: Life, Health (stock)	2558	-0.1368	Yes
...	...	...	...	...	...	...
204	Las Vegas Sands	LVS	Hotels, Casinos, Resorts	2545	0.1849	No
205	Ryder System	R	Trucking, Truck Leasing	2590	0.2	No
206	Avon Products	AVP	Household and Personal Products	2569	0.2054	No
207	Consolidated Edison	ED	Utilities: Gas and Electric	2598	0.224	No
208	PayPal Holdings	PYPL	Financial Data Services	82	0.2555	No
209	Wynn Resorts	WYNN	Hotels, Casinos, Resorts	2570	0.354	No
210	Enterprise Products Partners	EPD	Pipelines	2595	0.7209	No
211	Hilton Worldwide Holdings	HLT	Hotels, Casinos, Resorts	459	0.8044	Yes
212	Travelers Cos.	TRV	Insurance: Property and Casualty (Stock)	2598	1.2608	Yes
213	National Oilwell Varco	NOV	Oil and Gas Equipment, Services	2590	4.3469	No



Unpooled firm-specific estimates of article negativity with 95% confidence intervals sorted by effect size. Statistically significant coefficients printed in red. Effect sizes winsorized at [-10,10].

Figure A.4: Unpooled firm-specific estimates of tweet negativity

A.8 Stock return response model with prior brand strength

Table A.16: Stock return response model with prior brand strength

		Dependent Variable: Abnormal returns		
		Model 1	Model 2	Model 3
$log(ArticleVol + 1)$	β_1	-0.0001 (0.0002)	-0.0000 (0.0004)	-0.0001 (0.0002)
$ArticleNeg$	γ_1	-0.0037 (0.0086)	-0.0091 (0.0142)	-0.0037 (0.0087)
$log(TweetVol + 1)$	β_2	-0.0000 (0.0001)	-0.0000 (0.0001)	-0.0002 (0.0001)*
$TweetNeg$	γ_2	-0.0006 (0.0006)	-0.0006 (0.0006)	-0.0009 (0.0013)
$log(ArticleVol + 1) * ArticleNeg$	ζ_1	0.0007 (0.0135)	0.0048 (0.0236)	0.0011 (0.0136)
$log(TweetVol + 1) * TweetNeg$	ζ_2	0.0004 (0.0002)	0.0004 (0.0002)	0.0007 (0.0006)
$U\Delta CashETR$	ϕ	-0.0004 (0.0003)	-0.0004 (0.0003)	-0.0004 (0.0003)
$log(ArticleVol + 1) * U\Delta CashETR$	ρ_1	-0.0025 (0.0014)*	-0.0026 (0.0015)*	-0.0025 (0.0014)*
$ArticleNeg * U\Delta CashETR$	θ_1	0.0499 (0.0551)	0.0545 (0.0550)	0.0504 (0.0553)
$log(TweetVol + 1) * U\Delta CashETR$	ρ_2	0.0004 (0.0003)	0.0004 (0.0003)	0.0004 (0.0003)
$TweetNeg * U\Delta CashETR$	θ_2	0.0005 (0.0033)	0.0005 (0.0033)	0.0004 (0.0033)
$U\Delta ROA$	δ_1	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
$SalesGrowth$	δ_2	-0.0004 (0.0002)**	-0.0004 (0.0002)**	-0.0004 (0.0002)**
$afterHoliday = True$	δ_3	0.0005 (0.0003)*	0.0005 (0.0003)*	0.0005 (0.0003)*
$PriorBrandStrength$	δ_4		0.0000 (0.0000)	0.0000 (0.0000)
$log(ArticleVol + 1) * PriorBrandStrength$	δ_5		-0.0000 (0.0000)	
$ArticleNeg * PriorBrandStrength$	δ_6		0.0002 (0.0004)	
$log(ArticleVol + 1) * ArticleNeg * PriorBrandStrength$	δ_7		-0.0001 (0.0008)	
$log(TweetVol + 1) * PriorBrandStrength$	δ_8			0.0000 (0.0000)*
$TweetNeg * PriorBrandStrength$	δ_9			0.0000 (0.0001)
$log(TweetVol + 1) * TweetNeg * PriorBrandStrength$	δ_{10}			-0.0000 (0.0000)
N		247,940	247,940	247,940
Adj. R^2		0.040	0.040	0.040
Firm, weekday, and year FEs		yes	yes	yes

* p < .1, ** p < .05, *** p < .01

A.9 Regression equations for post-hoc trading volume models

$TradVol\ 1$:

$$\begin{aligned} log(\frac{TradVol_{i,t}}{PriorAvgTradVol(Month)_{i,t}}) = & \sum_{m=1}^{2} \beta_m * log(volume+1)_{m,i,t} + \sum_{m=1}^{2} \gamma_m * negativity_{m,i,t} \\ & + \phi * U\Delta CashETR_{i,t} \\ & + \sum_{m=1}^{2} [\zeta_m * log(volume+1)_{m,i,t} * negativity_{m,i,t}] \\ & + \sum_{m=1}^{2} [\rho_m * log(volume+1)_{m,i,t} * U\Delta CashETR_{i,t}] \\ & + \sum_{m=1}^{2} [\theta_m * negativity_{m,i,t} * U\Delta CashETR_{i,t}] \\ & + \sum_{j=1}^{5} \delta_j * controls_{j,i,t} + \eta_i + \eta_{weekday} + \eta_{year} + \varepsilon_{i,t} \end{aligned} \tag{A.3}$$

$TradVol\ 2$:

$$\begin{aligned} \frac{(TradVol_{i,t} - PriorAvgTradVol(Month)_{i,t})}{SharesOutstanding_{i,t}} = & \sum_{m=1}^{2} \beta_m * log(volume+1)_{m,i,t} + \sum_{m=1}^{2} \gamma_m * negativity_{m,i,t} \\ & + \phi * U\Delta CashETR_{i,t} \\ & + \sum_{m=1}^{2} [\zeta_m * log(volume+1)_{m,i,t} * negativity_{m,i,t}] \\ & + \sum_{m=1}^{2} [\rho_m * log(volume+1)_{m,i,t} * U\Delta CashETR_{i,t}] \\ & + \sum_{m=1}^{2} [\theta_m * negativity_{m,i,t} * U\Delta CashETR_{i,t}] \\ & + \sum_{j=1}^{5} \delta_j * controls_{j,i,t} + \eta_{weekday} + \eta_{year} + \varepsilon_{i,t} \end{aligned} \tag{A.4}$$

$TradVol\ 3$:

$$
\begin{aligned}
log(TradVol_{i,t}+1) = & \sum_{m=1}^{2} \beta_m * log(volume+1)_{m,i,t} + \sum_{m=1}^{2} \gamma_m * negativity_{m,i,t} \\
& + \phi * U\Delta CashETR_{i,t} \\
& + \sum_{m=1}^{2} [\zeta_m * log(volume+1)_{m,i,t} * negativity_{m,i,t}] \\
& + \sum_{m=1}^{2} [\rho_m * log(volume+1)_{m,i,t} * U\Delta CashETR_{i,t}] \\
& + \sum_{m=1}^{2} [\theta_m * negativity_{m,i,t} * U\Delta CashETR_{i,t}] \\
& + \sum_{j=1}^{5} \delta_j * controls_{j,i,t} + \eta_i + \eta_{weekday} + \eta_{year} + \varepsilon_{i,t}
\end{aligned}
\tag{A.5}
$$

with:	i	firm index
	t	trading day
	m	type of media (1 to 2; i.e., articles and tweets)
	$\eta_{i/weekday/year}$	firm, weekday, and year fixed effects
	$controls_j$	control variable j (1 to 5; i.e., $U\Delta ROA$, $SalesGrowth$, $afterHoliday = True$, $PriorAbnRet(Week)$, $PriorAbnRet(Month)$)

A.10 Trading volume models robustness checks

Table A.17: Trading volume models (3 day rolling sums (averages) for media attention)

		DV: Alternative operationalizations of trading volume		
		$TradVol\ 1$	$TradVol\ 2$	$TradVol\ 3$
$log(ArticleVol3day + 1)$	β_1	0.04 (0.00)***	101.10 (199.53)	0.06 (0.01)***
$ArticleNeg3day$	γ_1	1.05 (0.54)*	36,838.46 (16868.83)*	5.15 (2.10)**
$log(TweetVol3day + 1)$	β_2	0.01 (0.00)***	48.54 (24.54)*	0.01 (0.01)
$TweetNeg3day$	γ_2	0.03 (0.03)	241.78 (428.88)	0.22 (0.09)**
$log(ArticleVol3day + 1) * ArticleNeg3day$	ζ_1	-0.78 (0.35)**	-9,237.77 (6417.53)	-3.90 (1.71)**
$log(TweetVol3day + 1) * TweetNeg3day$	ζ_2	-0.04 (0.01)***	-533.01 (250.74)*	-0.15 (0.03)***
$U\Delta CashETR$	ϕ	-0.00 (0.00)	16.43 (63.67)	0.07 (0.05)
$log(ArticleVol3day + 1) * U\Delta CashETR$	ρ_1	-0.02 (0.03)	-936.64 (535.35)	-0.02 (0.09)
$ArticleNeg3day * U\Delta CashETR$	θ_1	2.52 (2.74)	97,816.01 (53751.05)*	4.50 (5.45)
$log(TweetVol3day + 1) * U\Delta CashETR$	ρ_2	0.00 (0.01)	-17.52 (157.00)	-0.04 (0.03)
$TweetNeg3day * U\Delta CashETR$	θ_2	-0.11 (0.16)	-639.37 (1820.73)	0.24 (0.40)
$U\Delta ROA$	δ_1	0.00 (0.00)	-13.17 (7.27)	-0.02 (0.00)***
$SalesGrowth$	δ_2	-0.00 (0.00)	19.89 (27.88)	-0.01 (0.01)
$afterHoliday = True$	δ_3	-0.15 (0.01)***	-1,075.25 (193.43)***	-0.15 (0.01)***
$PriorAbnRet(Week)$	δ_4	0.06 (0.04)	-390.77 (2421.20)	0.19 (0.03)***
$PriorAbnRet(Month)$	δ_5	-0.15 (0.02)***	-2,031.74 (337.21)***	-0.21 (0.04)***
N		992,214	992,196	993,766
Adj. R^2		0.009	0.003	0.880
Weekday, and year FEs		yes	yes	yes
Firm FEs		yes	no	yes
* p < .1, ** p < .05, *** p < .01				

DV TradVol 1: $log(TradVol/PriorAvgTradVol(Month))$

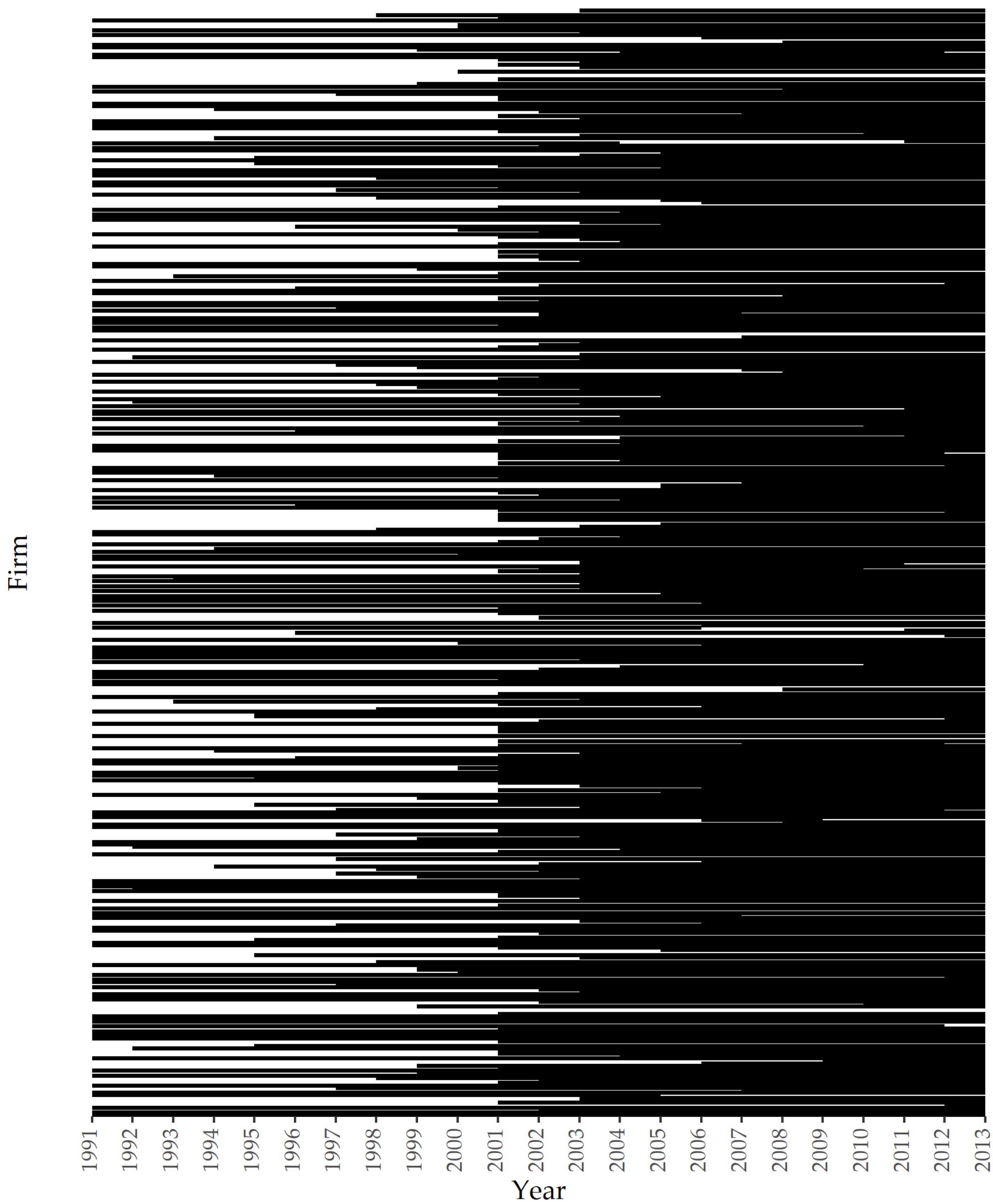
DV TradVol 2: $(TradVol - PriorAvgTradVol(Month))/SharesOutstanding$

DV TradVol 3: $log(TradVol + 1)$

B

Appendix Chapter 3

B.1 MSCI ESG Ratings - coverage of Fortune 500 firms



Data coverage of Fortune 500 firms (y-axis) in MSCI ESG Ratings data over time (x-axis). Covered firm-years marked with black bar.

Figure B.1: MSCI ESG Ratings - coverage of Fortune 500 firms

B.2 Regression results for models including lagged CSR/CSI

Table B.1: Regression results (including lagged measures of CSR/CSI)

	Dependent Variable: $log(Tobins\_Q)$		
	(1)	(2)	(3)
CSR	-0.017 (0.007)**	-0.018 (0.009)*	-0.010 (0.015)
CSI	-0.022 (0.010)*	-0.027 (0.012)**	-0.022 (0.011)*
$CashETR * CSR$	0.004 (0.079)	0.046 (0.095)	-0.285 (0.088)***
$CashETR * CSI$	0.158 (0.059)**	0.189 (0.102)*	0.228 (0.088)**
$LaggedCSR$	0.000 (0.011)	-0.013 (0.015)	0.015 (0.014)
$LaggedCSI$	0.009 (0.012)	-0.008 (0.009)	0.016 (0.016)
$CashETR * LaggedCSR$	0.041 (0.096)	-0.003 (0.045)	0.324 (0.122)**
$CashETR * LaggedCSI$	0.010 (0.048)	-0.131 (0.102)	-0.104 (0.090)
$CashETR$	-0.037 (0.054)	0.115 (0.056)*	0.123 (0.081)
ROA	0.037 (0.003)***	0.033 (0.003)***	0.041 (0.003)***
$Leverage$	-0.003 (0.001)**	-0.007 (0.001)***	-0.001 (0.001)
$log(Employees)$	-0.264 (0.021)***	-0.243 (0.022)***	-0.224 (0.038)***
N	3,366	2,923	1,843
Adj. R^2	0.915	0.886	0.918
Sample composition	Full	w/o Finance	B2C Focus
Firm FEs	yes	yes	yes
Year FEs	yes	yes	yes

* p < .1, ** p < .05, *** p < .01

B.3 Rating of B2C focus - wording of instructions

"Does the given company operate predominantly as a B2C company? In other words: Do private consumers purchase products/services directly from the company? To our understanding, firms like Apple, Disney, Facebook, or Coca-Cola are predominantly B2C firms, while Honeywell International, Cardinal Health, or General Electric would be examples of firms whose focus is rather not the B2C market."

C

Appendix Chapter 4

C.1 Literature review process

I follow the approach that Graf-Vlachy et al. (2020) use in their literature review for the time between 1997 and 2017, and which they explain in detail in their web appendix, to extend their list of papers to the years 2018 to 2023 (March). Using the EBSCO database, I conduct a keyword search of the words "media", "press", or "journalist" in the abstracts of all articles published in one of the publications listed in Table C.1. I screen the resulting articles for the following criteria: (1) Media coverage must only come from professional news organizations, (2) studies are only considered if they deal with media coverage of corporations; (3) studies must deal with earned medie coverage, not paid media coverage (such as advertising), and (4) the studies must include variables that pertain to the *topic* of firm media coverage.

Table C.1: Journals considered in the literature review

General Management
Academy of Management Annals
Academy of Management Journal
Academy of Management Review
Administrative Science Quarterly
American Economic Review
Econometrica
Experimental Economics
Journal of Economics & Management Strategy
Journal of Industrial Economics
Journal of Management
Journal of Management Studies
Journal of Political Economy
Management Science
Science
Strategic Management Journal
The RAND Journal of Economics

Organization and HR
Journal of Applied Psychology
Journal of Economic Behavior and Organization
Journal of International Business Studies
Journal of Labor Economics
Journal of Organizational Behavior
Journal of Public Administration Research and Theory
Leadership Quarterly
Organization Science
Organizational Behavior and Human Decision Processes
Organizational Research Methods
Personnel Psychology
The Journal of Strategic Information Systems

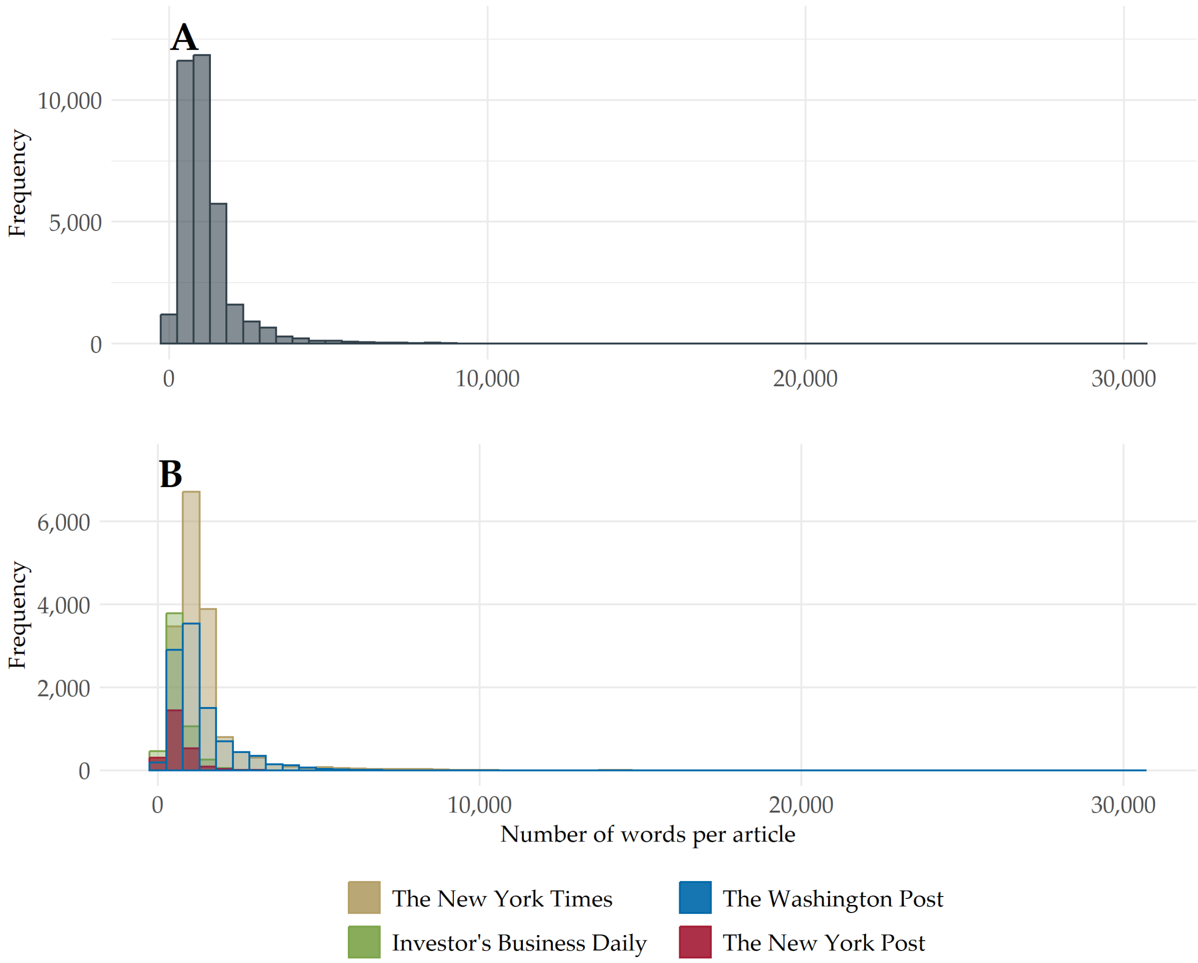
Innovation and Entrepreneurship
Entrepreneurship: Theory and Practice
Journal of Business Venturing
Journal of Product Innovation Management
Research Policy
Strategic Entrepreneurship Journal

Accounting
Accounting, Organizations and Society
Contemporary Accounting Research
European Accounting Review
Journal of Accounting and Economics
Journal of Accounting Research
Management Accounting Research
Review of Accounting Studies
The Accounting Review

Finance
Journal of Banking & Finance
Journal of Economic Dynamics & Control
Journal of Financial and Quantitative Analysis
Journal of Financial Economics
Journal of Financial Intermediation
Journal of Money, Credit and Banking
Review of Derivatives Research
Review of Finance
The Journal of Finance
The Review of Financial Studies

Marketing
International Journal of Research in Marketing
Journal of Consumer Psychology
Journal of Consumer Research
Journal of Marketing
Journal of Marketing Research
Journal of Retailing
Journal of Service Research
Journal of the Academy of Marketing Science
Marketing Science

C.2 Histograms of article lengths (number of words per article)



Panel A shows the data in aggregated form, Panel B shows the histograms broken down by news outlet.

Figure C.1: Histograms of article lengths (number of words per article; level-scale)

C.3 Full topic list

Table C.2: List of all 51 topics (focal model)

ID	Top 4 words or bigram	N	Share
1	stocks, stock, dow, percent	1,256	6.5%
2	energy, oil, climate, solar	1,116	5.7%
3	tax, taxes, cuts, obama	1,044	5.4%
4	republican, trump, clinton, campaign	1,002	5.2%
5	city, square, building, buildings	957	4.9%
6	electric, cars, car, vehicles	872	4.5%
7	china, tariffs, trade, chinese	790	4.1%
8	health, insurance, care, coverage	761	3.9%
9	page, israel, callimachi, islamic	669	3.4%
10	banks, bonuses, financial, bank	644	3.3%
11	drug, drugs, allergan, mylan	533	2.7%
12	ireland, luxembourg, european, tax	480	2.5%
13	mobile, cable, wireless, sprint	471	2.4%
14	ms, mother, neediest, film	456	2.3%
15	growth, economy, unemployment, jobs	423	2.2%
16	bonds, revenue bonds, general obligation, obligation	422	2.2%
17	free, www, library, nw	389	2.0%
18	privacy, data, european, antitrust	364	1.9%
19	area, terr, ave, lane	364	1.9%
20	lane, fairfax, cir, area	360	1.9%
21	area, corp, lane, ave	346	1.8%
22	mayor, cuomo, blasio, city	329	1.7%
23	eps, quarters, sales growth, eps growth	299	1.5%
24	corp, ave, area, lane	298	1.5%
25	greece, italy, euro, greek	290	1.5%
26	bil, rose, fell, mil	269	1.4%
27	foundation, philanthropy, charity, giving	255	1.3%
28	info, info www, starts, nights	249	1.3%
29	stores, sales, retailers, mart	239	1.2%
30	airlines, airline, flight, travel	237	1.2%
31	area, corp, road area, lane	231	1.2%
32	yankees, mets, cashman, season	225	1.2%
33	soda, obesity, drinks, sugar	223	1.1%
34	list price, bedrooms, price size, market list	190	1.0%
35	stadium, team, football, nfl	178	0.9%
36	wizards, knicks, nba, nets	177	0.9%
37	st, th st, th, corp	171	0.9%
38	listed, taxes listed, weeks year, lot taxes	170	0.9%
39	funds, fund, etfs, ibd	159	0.8%
40	tobacco, cigarettes, smoking, cigarette	153	0.8%
41	retirement, annuity, annuities, social security	152	0.8%
42	casino, gambling, casinos, gaming	150	0.8%
43	et al, associates, strategies, et	145	0.7%
44	mexico, brazil, venezuela, argentina	135	0.7%
45	yahoo, alibaba, mayer, ms mayer	134	0.7%
46	sales tax, sales taxes, retailers, collect	118	0.6%
47	appointed, district appointed, district, vice president	113	0.6%
48	fed, inflation, rates, yellen	109	0.6%
49	manafort, mr manafort, mueller, gates	108	0.6%
50	france, french, macron, mr macron	107	0.6%
51	teachers, schools, school, charter	103	0.5%

C.4 Representative articles for focal models

Table C.3: Representative articles for focal topics

Topic	Representative article
Topic 1: "Capital markets"	https://www.washingtonpost.com/business/economy/2016/12/30/fc0ff4ee-cebd-11e6-a87f-b917067331bb_story.html (last access: April 11, 2023)
Topic 3: "Tax cuts"	https://www.nytimes.com/2015/09/03/upshot/eight-things-to-watch-for-in-donald-trumps-tax-plan.html (last access: April 11, 2023)
Topic 4: "US elections"	https://www.washingtonpost.com/powerpost/primary-elections-minnesota-wisconsin-vermont-connecticut/2018/08/13/94646364-9f29-11e8-8e87-c869fe70a721_story.html (last access: April 11, 2023)
Topic 10: "Banking crisis"	www.washingtonpost.com/business/economy/divided-house-passes-major-bank-deregulation-bill-sends-to-trump/2018/05/22/6f3bb562-5dd2-11e8-a4a4-c070ef53f315_story.html (last access: April 11, 2023)
Topic 12: "Corporate tax avoidance"	https://www.nytimes.com/2017/10/04/business/dealbook/europe-apple-amazon-taxes.html (last access: April 11, 2023)

C.5 UMAP representations of focal topics

In an effort to visually show the results of the topic model, I rerun the UMAP algorithm reducing the article embeddings to the 2-dimensional space, plot all articles in a point diagram and color the observations belongig to one of the focal topics in Figure C.2. Note that this 2D-representation is just for illustrative purposes. The HDBSCAN clustering of the focal model is based on five UMAP-dimensions, which would be impossible to visualize graphically. All focal topics are clustered relatively close together with *"Corporate tax avoidance"* being the most diffuse topic in the two-dimensional space. It seems like the reduction from five to two embedding dimensions leads to a loss of information about *"Corporate tax avoidance"* that is relevant for the HDBSCAN clustering algorithm. The consequence is that in two-dimensional representation the reddish colored points (*"Corporate tax avoidance"*) are spread over a relatively wide area in Figure C.2. Looking at the distances between the cluster centroids, it can be seen that the topics *"US elections"* and *"Tax cuts"* are semantically close together, which seems face valid since both topics have politics as a common theme. A small cluster lies at the extreme left edge of Figure C.2, far from the bulk of the observations. I have identified this cluster as "Weddings & Charity" because it contains mostly marriage announcements as well as reports from "The Neediest Cases Fund" section of *The New York Times*, in which, probably rather coincidentally, company names are mentioned together with the term "tax". The fact that this exotic topic stands out so clearly graphically speaks for the suitability of the embedding technique for capturing the semantic meaning of the documents.

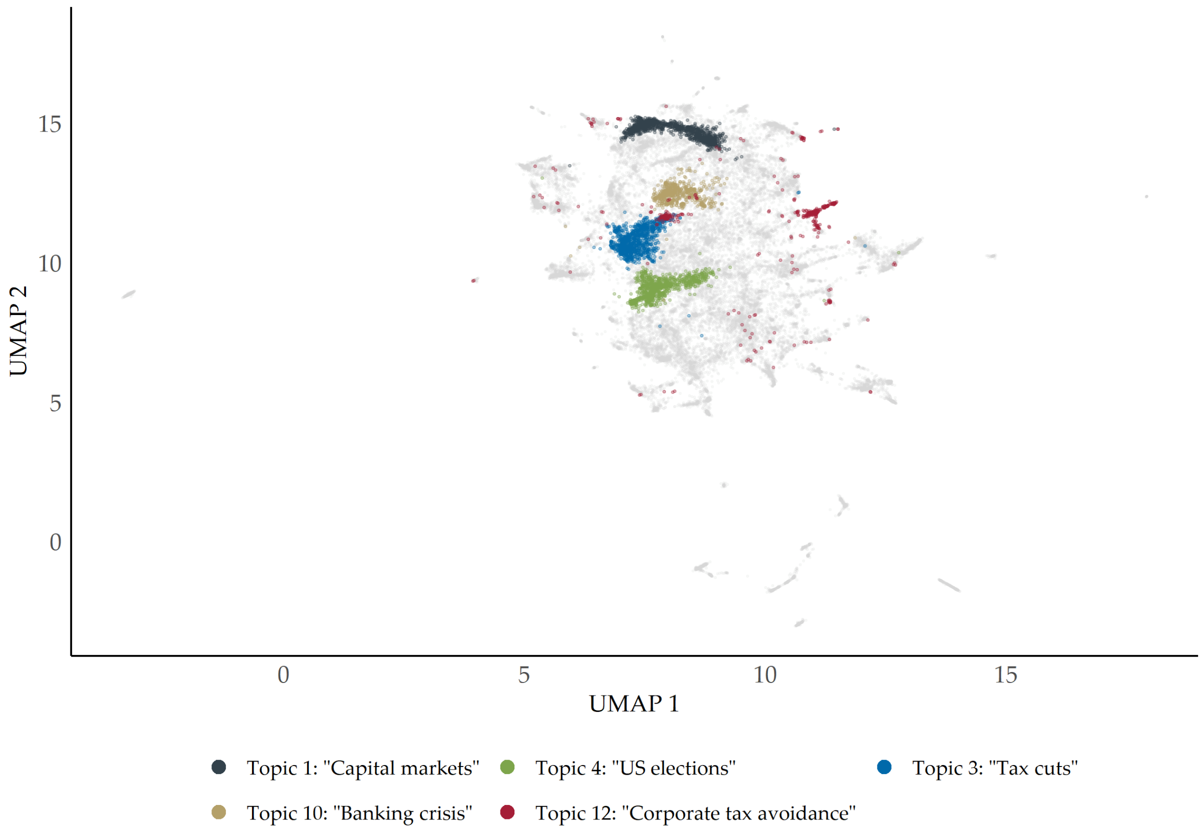


Figure C.2: Two-dimensional UMAP representation of focal topics

C.6 Topics over time (Investor's Business Daily)

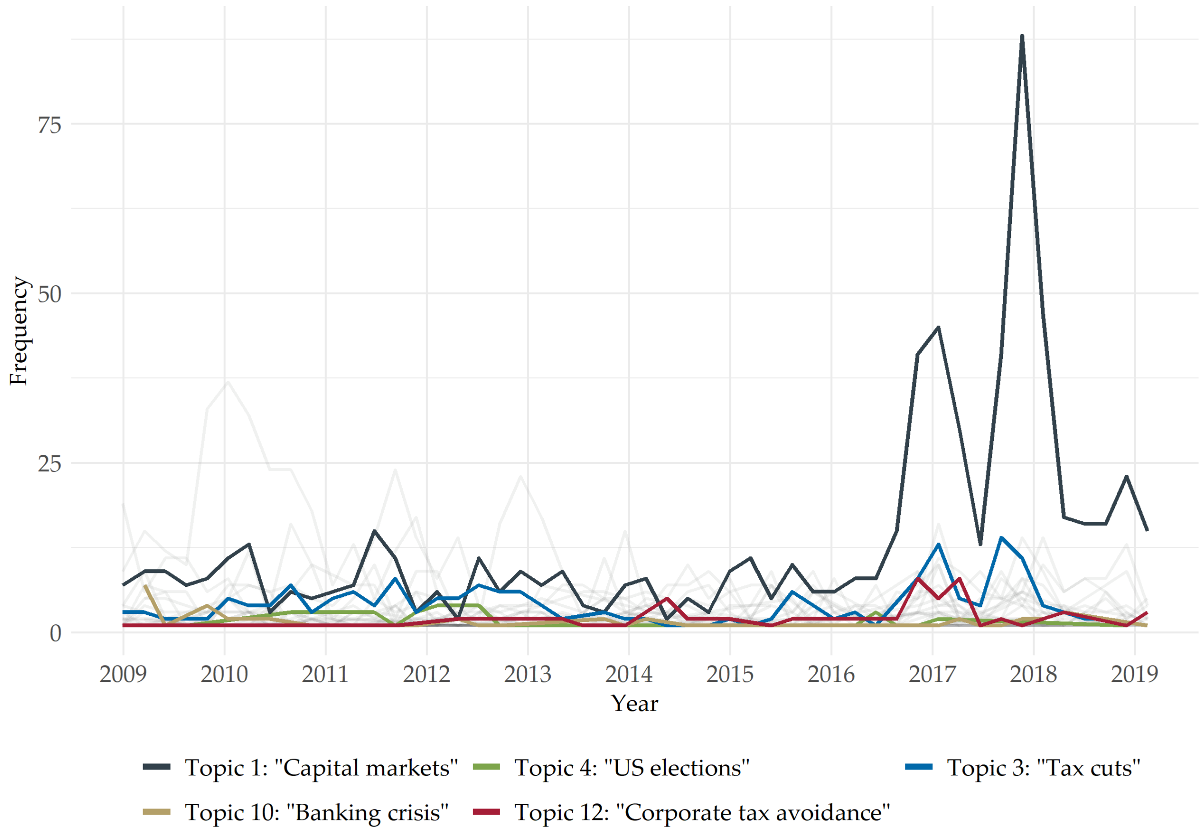


Figure C.3: Topics over time (Investor's Business Daily)

C.7 Time-specific topic representations for the "Topic 4: US elections"

Table C.4: Time-specific topic representations for "Topic 4: US elections"

Timestamp	Time-specific topic representation (Top 5 words or bigrams)
2008-12-28	tapper, anuzis, saltsman, neas, bowling
2009-03-17	ms gillibrand, gillibrand, mr frederick, tobacco, president mccain
2009-05-31	palin, mccain, mcdonnell, deeds, lieberman
2009-08-15	mcdonnell, deeds, titus, thesis, stolle
2009-10-29	crist, scozzafava, rubio, party, republican
2010-01-13	gillibrand, palin, devore, mr campbell, mr brady
2010-03-29	fimian, favreau, tea party, lesser, mr parnell
2010-06-12	murkowski, dudley, palin, freedomworks, tea party
2010-08-27	nickles, murkowski, mcmahon, republican, mr boehner
2010-11-10	runyan, mr grayson, rep elect, runyan said, layton
2011-01-25	applause, walker, hatch, tonight, america
2011-04-10	palin, ms palin, applause, mrs bachmann, bachmann
2011-06-25	wildmon, mr sharpton, mr wildmon, ms haley, haley
2011-09-08	cain, perry, mr harwood, romney, ms bartiromo
2011-11-22	gingrich, romney, newt, santorum, mr gingrich
2012-02-06	boehner, romney, obama, grand bargain, santorum
2012-04-21	nixon, watergate, haldeman, romney, burning man
2012-07-06	romney, ryan, obama, convention, campaign
2012-09-19	romney, mr lehrer, lehrer, mr romney, obama
2012-12-03	cheers applause, cheers, applause, mr boehner, jacobson
2013-02-17	foxx, mara, strouse, warner, mcdonnell
2013-05-03	bardella, issa, cuccinelli, mr enzi, mr alter
2013-07-18	mizeur, applause, greentech, vedp, mcauliffe
2013-10-01	cuccinelli, byrne, coralville, virginia, west virginia
2013-12-16	mr paul, paul, rand, ron paul, republican
2014-03-01	vihstadt, mr shannon, dole, palin, howze
2014-05-15	mizeur, mcdaniel, brown, cantor, mccrory
2014-07-30	orman, pryor, hogan, van putte, putte
2014-10-13	steyer, malloy, mr malloy, comstock, peroutka
2014-12-28	huckabee, mr murdoch, romney, christie, murdoch
2015-03-13	carson, huckabee, bush, republican, mr bush
2015-05-28	sanders, jindal, murphy, brat, bush
2015-08-11	cooper, sanders, malley, clinton, cooper senator
2015-10-25	rubio, applause, thank, cruz, senator
2016-01-09	applause, sanders, rubio, clinton, cruz
2016-03-24	sanders, clinton, blitzer, applause, senator sanders
2016-06-08	trump, mr weaver, clinton, pence, convention
2016-08-22	clinton, crooked, trump, crooked crooked, secretary clinton
2016-11-05	trump, president elect, elect, clinton, mr trump
2017-01-20	trump, schumer, democrats, applause, chaffetz
2017-04-05	trump, mr flynn, flynn, mr trump, mr
2017-06-20	stryk, lewandowski, trump, yohai, mr yohai
2017-09-03	papadopoulos, guadagno, mr papadopoulos, ms guadagno, manafort
2017-11-18	trump, inaudible, schmidt, mr shapiro, collusion
2018-02-01	murkowski, manafort, trump, gates, mueller
2018-04-17	trump, democratic, mr pence, mr león, renacci
2018-07-02	manafort, kemp, mr manafort, mr kemp, mr stewart
2018-09-15	gillum, mr gillum, republican, trump, rourke
2018-11-30	schultz, democrats, democratic, trump, abrams
2019-02-13	mueller, northam, trump, democratic, special counsel

C.8 Alternative transformer models

Table C.5: Alternative model specifications with different transformer models

		Focal model	**Variant C**	**Variant D**
SBERT	*transformer_model*	all-MiniLM-L6-v2	all-distilroberta-v1	all-mpnet-base-v2
UMAP	*n_neighbors*	30	30	30
	n_components	5	5	5
HDBSCAN	*min_cluster_size*	100	150	150
	min_samples	100	150	150
Topic descriptives	*# of outliers*	15,210	15,677	13,266
	# of topics	51	38	34
	Average topic size	381.1	499.2	628.8
Sizes of focal topics	*"Capital markets"*	1,256	2,006 + 655[a]	673 + 644[d]
	"US elections"	1,002	1,061	6,630[e]
	"Tax cuts"	1,044	460	201
	"Banking crisis"	644	386 + 206[b]	970
	"Corporate tax avoidance"	480	216 + 180[c]	232 + 179[f]

[a] I understand both topics 1 and 10 to pertain to capital markets (see Table C.6).
[b] I understand both topics 17 and 35 to pertain to the banking crisis (see Table C.6).
[c] I understand both topics 33 and 36 to pertain to corporate tax avoidance (see Table C.6).
[d] I understand both topics 8 and 9 to pertain to capital markets (see Table C.7).
[e] Topic 1 is very broad and diffuse, and it seems to cover the US elections, among other topics (see Table C.7).
[f] I understand both topics 27 and 31 to pertain to corporate tax avoidance (see Table C.7).

Table C.6: List of all 38 topics (alternative model: Variant C)

ID	Global topic representation (Top 10 words or bigrams)	N	Share
1	earnings, stock, sales, quarter, shares, ibd, share, cents, revenue, growth	2,006	10.6%
2	page, briefing, morning, times, president, new, trump, president trump, york times, islamic	1,101	5.8%
3	area, corp, ave, lane, st, michael, robert, john, james, terr	1,085	5.7%
4	republican, campaign, clinton, trump, party, governor, romney, democratic, voters, mr	1,061	5.6%
5	energy, oil, climate, solar, carbon, gas, coal, climate change, wind, power	1,053	5.6%
6	team, season, stadium, league, yankees, players, game, teams, games, sports	915	4.8%
7	bil, rose, fell, mil, views, pres, cents, eps, sales, shares	824	4.3%
8	electric, cars, car, vehicles, volt, ford, battery, model, vehicle, electric cars	809	4.3%
9	health, insurance, care, coverage, health care, insurers, obamacare, premiums, health insurance, medicare	681	3.6%
10	percent, stocks, dow, index, points percent, stock, market, points, investors, rose	655	3.5%
11	china, trade, tariffs, chinese, united states, united, trump, states, american, steel	592	3.1%
12	bonds, revenue bonds, general obligation, obligation, refinancing, refinancing bonds, authority million, bonds competitive, million, million general	492	2.6%
13	listed, taxes listed, room, lot taxes, weeks year, garage, car garage, weeks, taxes, acre lot	476	2.5%
14	tax, taxes, income, republicans, cuts, capital gains, budget, obama, boehner, rate	460	2.4%
15	growth, economy, jobs, unemployment, labor, economists, economic, rate, job, percent	440	2.3%
16	police, stolen, block, avenatti, court, mr avenatti, sheriff, judge, mr, said	389	2.1%
17	billion, settlement, bank, company, million, firm, percent, falcone, court, financial	386	2.0%
18	drug, drugs, astrazeneca, valeant, mylan, shire, cancer, pharmaceutical, allergan, generic	355	1.9%
19	privacy, data, european, information, users, antitrust, internet, search, europe, tech	354	1.9%
20	lane, area, st, fairfax, corp, cir, michael, james, john, david	348	1.8%
21	airlines, airline, airbus, planes, flight, ryanair, passengers, aircraft, plane, carriers	343	1.8%
22	city, new york, york, cuomo, new, headquarters, cities, incentives, island city, seattle	334	1.8%
23	free, www, library, center, nw, warrenton, registration, registration required, saturday, noon	326	1.7%
24	cable, tv, wireless, charter, subscribers, mobile, malone, espn, directv, networks	314	1.7%
25	info, info www, trip, round trip, nights, travel, starts, cruise, night, person double	286	1.5%
26	neediest, neediest cases, ms, cases fund, times neediest, new york, york, cases, mother, fund	270	1.4%
27	eps, quarters, sales growth, eps growth, past quarters, maker, qtrs, growth, sales, earnings	265	1.4%
28	corp, ave, area, lane, st, th ave, mortgage, national mortgage, federal national, mortgage association	258	1.4%
29	puerto, puerto rico, rico, brazil, mexico, oil, government, mexican, corruption, cuba	257	1.4%
30	film, movie, minutes contains, contains, area theaters, movies, theaters, films, pg minutes, minutes	248	1.3%
31	soda, food, obesity, drinks, sugar, sugary, calories, beverage, calorie, beverages	239	1.3%
32	square, square feet, building, feet, city, space, hudson yards, foot, square foot, yards	222	1.2%
33	ireland, luxembourg, european, tax, taxes, multinational, european union, corporate, companies, profits	216	1.1%
34	home, homes, buyers, mortgage, housing, real estate, property, lenders, mortgages, foreclosure	210	1.1%
35	banks, bonuses, financial, bailout, tarp, dodd, treasury, wall street, wall, crisis	206	1.1%
36	profits, corporate, tax, taxes, companies, overseas, corporate tax, rate, tax rate, corporations	180	0.9%
37	retirement, annuity, annuities, savings, account, roth, money, insurance, financial, accounts	158	0.8%
38	philanthropy, foundation, charity, giving, charitable, zuckerberg, nonprofit, charities, philanthropic, gates	154	0.8%

Table C.7: List of all 34 topics (alternative model: Variant D)

ID	Global topic representation (Top 10 words or bigrams)	N	Share
1	mr, trump, new, city, said, new york, people, president, campaign, party	6,630	31.0%
2	energy, oil, climate, carbon, solar, gas, coal, climate change, wind, power	1,158	5.4%
3	team, season, players, game, stadium, league, yankees, sports, casino, gambling	1,126	5.3%
4	banks, financial, bank, bonuses, wall street, wall, billion, goldman, trading, compensation	970	4.5%
5	electric, cars, car, vehicles, volt, ford, battery, model, vehicle, musk	888	4.2%
6	china, trade, tariffs, chinese, trump, united states, united, states, american, mr	838	3.9%
7	health, insurance, care, health care, coverage, insurers, obamacare, premiums, health insurance, medicare	770	3.6%
8	percent, stocks, dow, index, points percent, stock, market, investors, points, rose	673	3.1%
9	bil, rose, fell, mil, views, pres, eps, cents, sales, shares	644	3.0%
10	privacy, data, european, tech, antitrust, internet, companies, users, europe, search	523	2.4%
11	listed, taxes listed, room, lot taxes, weeks year, garage, car garage, weeks, acre lot, taxes	485	2.3%
12	cable, wireless, mobile, sprint, vodafone, subscribers, tv, billion, charter, deal	484	2.3%
13	bonds, revenue bonds, general obligation, obligation, refinancing	417	2.0%
14	buy point, stock, buy, base, volume, earnings, ibd, shares, quarter, cents	400	1.9%
15	drug, astrazeneca, shire, valeant, drugs, allergan, billion, deal, pharmaceuticals, company	399	1.9%
16	corp, ave, area, lane, st, mortgage, th ave, federal national, national mortgage, mortgage association	380	1.8%
17	growth, economy, jobs, unemployment, economists, spending, percent, economic, labor, rate	372	1.7%
18	lane, area, st, fairfax, corp, cir, michael, john, james, david	357	1.7%
19	free, www, library, nw, center, warrenton, registration, registration required, saturday, noon	328	1.5%
20	area, corp, lane, ave, michael, way, john, robert, james, william	322	1.5%
21	appointed, district appointed, district, vice president, vice, associates, strategies, group, et al, et	312	1.5%
22	tax, income, taxes, capital gains, gains, rate, buffett, tax rate, capital, deductions	291	1.4%
23	eps, quarters, sales growth, eps growth, past quarters, maker, qtrs, growth, sales, earnings	279	1.3%
24	area, terr, ave, corp, lane, st, michael, cir, robert, john	276	1.3%
25	soda, food, obesity, sugar, drinks, calories, sugary, beverage, calorie, beverages	263	1.2%
26	info, info www, round trip, trip, nights, starts, travel, person double, night, www	255	1.2%
27	ireland, luxembourg, tax, european, corporate, taxes, profits, multinational, companies, irish	232	1.1%
28	area, corp, lane, road area, prince frederick, charles, st, beach area, mortgage, mary	230	1.1%
29	retirement, annuity, money, annuities, social security, savings, financial, pension, account, insurance	209	1.0%
30	budget, debt, cuts, spending, republicans, obama, deficit, fiscal, house, boehner	201	0.9%
31	profits, tax, corporate, taxes, overseas, companies, corporate tax, rate, tax rate, corporations	179	0.8%
32	philanthropy, foundation, charity, giving, charitable, gates, nonprofit, zuckerberg, philanthropic, charities	169	0.8%
33	airlines, airline, travel, flight, travelers, fees, passengers, ticket, fares, airport	160	0.7%
34	brazil, mexico, cuba, oil, corruption, pemex, venezuela, rousseff, government, argentina	159	0.7%