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# Digital and Sustainable Finance: New Drivers for Market Efficiency

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*Digital and Sustainable Finance:*
*New Drivers for Market Efficiency*

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# Chapter 1

# Introduction

## 1.1 Introduction

Capital markets aggregate information. Since the famous market efficiency hypothesis of Fama (1970), it has been the subject of general and scientific debates whether this process of collecting and pricing of data is so efficient that all available information is aggregated in the price. In this context, the pricing of new information cannot be complete across all times and markets, because society, the economy, technology, as well as other circumstances such as the climate are constantly changing. This leads perpetually to different perceptions and expectations about the future and therefore changing prices. However, the basic assumption that financial markets are a conglomeration of different expectations about products, goods, firms, technologies, or even societal projections has been valid for several decades (Hayek, 1945). As both markets and their participants became more sophisticated regarding production, dissemination, and analysis of information and the dissection thereof, the quality of prices as market signals should improve and have feedback effects on the real economy (Goldstein, 2023).

This dissertation addresses two important drivers of today's financial markets, digitization as well as sustainability. At a high level of abstraction, the studies presented in the following examine the effectiveness of information in today's financial markets and explore both the underlying causes and potential solutions to current challenges. Any progress or innovation comes at the trade-off of changing the economic landscape, their participants, and the expectations about the future. This creative destruction is closely aligned with capitalism itself, where new ideas and technologies replace outdated ones, driving economic progress through competition and renewal (Schumpeter, 1912). Financial markets, as a key instrument for information aggregation therefore reflect the landscape within economics, while the participants in capital markets need to constantly adapt to the ever changing nature of human progress (Lo, 2004). On the one hand, technological advances in areas such as cryptography or artificial intelligence offer significant efficiency gains that can be exploited. On the other hand, the critical issue of creating a sustainable financial system must be addressed, highlighting the need to consider the broader impact of financial activities and to find solutions that balance economic growth with environmental and social considerations.

As the economy and its participants continuously evolve, the struggle for complete information within financial markets is never finished. At the same time investors, regulators, and researchers try to capture and understand the feedback effects of prices (Goldstein, 2023). This is one of the striking commonalities between these seemingly so distant fields of digital and sustainable finance. Both seek to find these feedback effects within economics and try to guide these important topics. Regarding sustainability, investors and regulators seek to enforce transparency and reporting within corporations and in economics in total. On the other hand, within digital finance, especially in the blockchain community, there are continuous efforts to make finance and its processes as transparent as possible. In these processes, prices serve as signals guiding society towards what is useful, what is necessary, and what is worthwhile. It is the task of markets as well as research, especially in economics, to analyze what separates the wheat from the chaff in the sense of what will bring future welfare gains for society and what should be set aside for human progress. The interest of the general public, academics, and practitioners alike in the possibilities of welfare creation put these topics at the top of the agenda of decision-makers. Therefore, both topics change the economic landscape, as well as future expectations about how and what to pursue within the economic endeavor. The studies in this dissertation shed light on key aspects of these significant challenges, offering insights on how to navigate this evolving landscape while highlighting important factors and feedback effects in the field of finance and economics.

## 1.2 Digital Finance

The pledge of digitization in finance, in all aspects, is the transformation of processes, decision making or even the transmission of assets into the digital realm. The goal is that procedures like payments, financial services, investments, and the assets themselves become faster, more cost efficient, more transparent, and easier to access for investors and stakeholders (Yermack, 2017; Lambert et al., 2022; Gargano and Rossi, 2024). Hence, it is unsurprising that academics in recent decades have focused extensively on the impacts of digitizing traditional financial concepts and products.

However, the definition of digital finance is difficult to come by. More traditionally, there is the notion of simply moving traditional financial services, such as payments, banking, and investments into the digital world. This is often connected with new technologies and improvement in terms of automatizing certain aspects within the value chain of financial services or for the convenience of the user, for example in investing or taking out a loan (Chen et al., 2019). The implementation of these so called financial technologies coined the term FinTech, where certain financial services are connected or shifted to the digital world. However, a binding legal definition of this term does not exist to date. In this dissertation, the taxonomy and corresponding definitions established by Dorfleitner et al. (2017) are followed. A core aspect of the definition of FinTechs is or was the disruption of financial services through technological innovation (Gomber et al., 2017, 2018). This disruptive character is often accompanied by exceptional growth in the number of users and revenue, which is documented in chapter 3. But there is the recent tendency of FinTechs being either integrated into traditional companies within the financial industry or working closely together with them. Since the business models of FinTechs have matured, as a category of business within financial markets, it is becoming increasingly difficult to separate them from traditional financial services. This is underscored by the fact that traditional players are adopting the technology themselves. The manifold academic studies about this segment of financial markets emphasize its importance, as illustrated and summed up by Alt et al. (2024). As a result, fintechs in Germany are crucial as they enhance market efficiency and adapt to feedback effects, driving innovation in the financial sector.

The landscape of digital finance experienced another profound shift with the introduction of blockchain technology, catalyzing the digitization of financial services. One important milestone thereof is undoubtedly the famous proof of concept with Bitcoin by Nakamoto (2008). The concept of the distributed ledger technology (DLT), for which Bitcoin is just one example, has a significant impact on capital markets and for the field of finance in general. The aim of blockchain enthusiasts is to abolish traditional financial intermediaries and institutions by creating transparent and decentralized financial markets. The distributed ledger technology allows to disrupt traditional intermediaries by delivering the foundation for disintermediation through its built in traceability (Bollaert et al., 2021). The blockchain acts as a digital version of a cash book or ever evolving balance sheet. It fuels the hopes of investors and individuals globally to achieve a fair, open, and democratic financial system which is called decentralized finance (DeFi). The core ideal of DeFi is that no institution or individual should hold the power of decision over key aspects of finance. Every information and transaction should be available to everybody to make informed decisions. Enabled by the technological advances of the blockchain, new ecosystems emerge which strive to replace or imitate different traditional functions of capital markets (Aquilina et al., 2024).

An additional significant milestone in the digitization of finance is the implementation of smart contracts, automated computer code which executes at a given time under defined circumstances without human intervention. Unlike Bitcoin, the Ethereum blockchain is able to perform as a pure payment system with its native crypto-currency Ether and to serve as a platform for smart contracts (Buterin, 2013). This built-in functionality enables automation of various transactions especially in finance and has tremendous potential to disrupt the industry, while also allowing for transparent and democratic consensus mechanisms (Chen et al., 2019). Especially these consensus mechanisms, often implemented in so called decentralized autonomous organizations (DAOs), enable participants to have a vote within their ecosystem and transparently alter the nature of the blockchain project (Laturnus, 2023). The transparency of decision making in combination with traceability of transactions and decisions is an important innovation in finance, where rules are traditionally set by financial institutions and regulators, but not by its participants. One example for the functionality of DAOs is the decentralized exchange Uniswap, invented by Adams (2018), and currently running on its third version (Adams et al., 2021). It utilizes so called liquidity pools, where investors place crypto-currencies and stable coin pairs, which makes traditional market makers obsolete. In regards to trading volume, protocols like Uniswap are now comparable to traditional financial exchanges, but controlled in democratic manner by the DAO. Its protocols are open-access and are utilized in different projects. The decentralized approach of blockchain technology including the transparency of transactions enables researchers and practitioners to analyze investors' behavior in more detail than in traditional financial systems. Another remarkable feature is the ability to split the blockchain according to the wishes of competing groups within a DAO, in a process called forking. Each member can decide which protocol to use and the competition between protocols will show, which approach will endure. In this dissertation, the investment opportunities are demonstrated in real estate through real estate tokenization in chapter 2, and for classical investments through the tokenization of securities in chapter 4.

Traditionally, no improvement comes without trade-offs. The pseudonymity of the blockchain technology scared the public and regulators and led to many incidents of illegal behavior financed with crypto-currencies. Also, there are many cases of wasteful or even fraudulent actions and investment propositions within the crypto space. But looking at the total history of markets, this is a normal process at the beginning of an emerging technology, comparable for example with the beginning of the dotcom bubble, where many firms achieved high valuations without having a sustainable business model (Ljungqvist et al., 2006; Franzke, 2004). Still, for the reputation of blockchain technology, these aspects hinder adoptation and even regulatory and societal acceptance. Foley et al. (2019) estimate that 46 percent of all Bitcoin transactions per year with an equivalent of around \$ 76 billion are used for illegal activities. Besides funding illegal activities, there is also the problem of fraud and stealing crypto-currencies within the ecosystem itself, which is analyzed by Hornuf et al. (2023). Another aspect of crypto-currencies is the tendency to organize on social media to drive up prices and quickly sell afterwards, so called pump and dump schemes (Hamrick et al., 2021). Thereby, the majority of non-sophisticated investors achieve significant negative returns, however they still frequently engage in these schemes for the huge upside potential of correct timing and for a sense of group belonging (Dhawan and Putnins, 2023).

The advances in machine learning and generative artificial intelligence represent another important aspect of the digitization of finance. The most important ability of artificial intelligence is the recognition of patterns, whether it is within data or text. One aspect is the combination of big data and machine learning models for more powerful predictions in, for example, stock markets (Brunnermeier, 2021). Murray et al. (2024) use financial models for predicting stock returns, questioning thereby the validity of the efficient market hypothesis, and find that, with the use of machine learning, technical analysis and charting can still be useful. Chen and McCoy (2024) use machine-learning techniques for the handling of missing values in portfolio construction. The implementation of artificial intelligence is not only important for academia and capital markets, but also within the economy. Babina et al. (2024) analyze economic effects of artificial intelligence adoption in firms and find that firms experience higher growth in sales, employment, and market valuations through increased product innovation with the implementation of artificial intelligence. The higher predictive power comes at the cost of missing explainability of the models and algorithms used. Still, there are promising approaches and attempts to clarify the black box nature of machine learning (Lundberg et al., 2020; Kellner et al., 2022; Nagl et al., 2022; Büchel et al., 2022). In chapter 5 a new approach for quantifying language is proposed in order to explain investors' reaction to the disclosure of new information.

All together, the increasing speed of shifting financial infrastructure into the digital realm, the promising attempts of transparency and consensus within the blockchain technology, as well as the predictive power of utilizing artificial intelligence offer various improvements for feedback effects within prices, for market efficiency as a whole, and for the improvement of capital markets. At the same time, it is the role of academia to observe and research the topics mentioned above, to gain new insights on how these new dynamics function, and to guide practitioners and regulators along the way. This guidance aims to improve the implementation of these powerful technological aspects of finance, not only for the betterment of financial markets but for the benefit of society as a whole.

## 1.3 Sustainable Finance

Besides the understandable desire of efficiency within capital markets and the whole economy through the promises of digitization, economic growth as its sole purpose at the expense of the well-being of societies and the planet itself is not appealing. It even carries the danger of eroding the societal acceptance of the current economic models despite the tremendous welfare gains in the past decades. Since resources are not abundant and endless by any means, societies and economies should logically focus on a sustainable, meaning enduring, way of ensuring prosperity for future generations.

The first definition of sustainability, coming from forestry, means not cutting more trees than there will grow (von Carlowitz and von Rohr, 1732). The more abstract way of thinking about sustainability is not eroding the foundation for a prosperous future in a trade-off for short-term gains. However, the problem of the current setup of prices within markets, which economists have already discovered decades ago, is that prices do not necessarily reflect all costs. These externalities, however, influence future welfare. For example, the emission of greenhouse gas and the increasing temperatures associated with climate change have a negative impact on GDP growth, which is shown by Bilal and Kaenzig (2024) or Kahn et al. (2021).

The United Nations, with the Brundtland report, came to the conclusion that economies are nested within societies, and therefore need to take care of the economical, the ecological, and the social dimension (Brundtland, 1987). Although still decades away from implementation, this is one of the first attempts to address the now famous term of Environmental, Social, and Governance (ESG) aspects. Since the guidelines for the economical part were already set up by the rule of markets, competition, prices, and accounting standards, there was a need to define what the ecological and social dimensions imply for economic endeavors within a capitalist system. Within strategic management, approaches changed from pure shareholder value maximization (Friedman, 1970) to a stakeholder-oriented approach (Freeman, 1984). That means that not only consumers and owners should be prioritized by firms, but legitimate stakeholders, i.e. groups and individuals that are affected by or can affect the firm. However, the internalization of external costs is a complicated endeavor. It requires a global understanding and willingness to price sustainability-related factors. It can also affect the competitiveness of firms, industries, and countries, as well as cause unintended redistributive effects. Therefore, progress in pricing externalities has recently stagnated. Still, since the ecological and social ramifications of economic activities are undeniable, financial markets began to quantify the sustainability of companies in terms of ESG scores.

The underlying idea as well as the definition of the measurement of sustainability is crucially important. If there is no universal agreed-upon goal, it is impossible for the complex interplay of societies and economies to aim for a sustainable future. The objective should be to measure how endeavors of a company and ultimately the economic activities in total are changing, in terms of the stakeholder approach, the environment, the social community, and the company itself regarding governance. However, there needs to be the willingness to bear the consequences of sustainable behavior. This implies that certain business practices or even industries will have to undergo radical changes to survive in a sustainable economy. Since the internalization of externalities was not widely enforced by regulators, finance academia focused on how firms, measured in terms of ESG or other measurement approaches, differ across various dimensions. If firms which actively engage in sustainable practices or corporate social responsibility (CSR) would also experience competitive advantages regarding their financial performance, capital markets would automatically allocate more financial resources to sustainable firms. Financial markets would then incentivize further efforts of companies towards CSR. Therefore, the hypothesis of "doing well by doing good", namely increasing future financial performance measures with engagement in CSR, would be a desirable solution for capital markets (Orlitzky et al., 2003; Kempf and Osthoff, 2007; Krüger, 2015; Flammer, 2021). The question of if and how CSR is affecting financial performance is a constant matter of academic debate. One strand of literature associates it with reputational advantages, leading to a stronger association with stakeholders, resulting in the creation of intangible, but valuable assets within the firm (McWilliams and Siegel, 2000; Luo and Bhattacharya, 2006). Other empirical work focuses on a reduced exposure of high ESG firms to systematic or unsystematic risk (Godfrey, 2005; Godfrey et al., 2009; Albuquerque et al., 2019; Dorfleitner and Grebler, 2022), while other studies analyze the benefits of ESG through reduced costs of capital (Goss and Roberts, 2011; El Ghoul et al., 2011). The argued effect thereby is that extended CSR reporting can reduce information asymmetries between a firm's stakeholders and its corporate management (Harrison et al., 2010). Another important aspect is the hedging potential of sustainable firms against climate-related risks (Engle et al., 2020; Ilhan et al., 2021). However, the connection of corporate financial performance and carbon emissions shows a positive correlation between financial performance and carbon emissions (Bolton and Kacperczyk, 2021, 2022), while Aswani et al. (2024) show that this effect depends on the measurement of emissions and carbon intensity.

Pástor et al. (2021) conclude that in equilibrium, high-ESG assets should have lower expected returns, since investors desire utility from sustainable investments and can hedge against climate risks. Gantchev et al. (2024) show that mutual funds, which engage in sustainability-driven trades after the introduction of Morningstar's sustainability ratings attract more inflows, but at the cost of their financial performance. From the point of view of shareholder value maximization, engagement in CSR activities cannot create value for the company and therefore, these firms need to have weaker financial performance (Renneboog et al., 2008; Barnea and Rubin, 2010; Bolton and Kacperczyk, 2021). Since managers nevertheless engage in CSR activities, several studies see the reason in reputational and private gains of executives (Brown et al., 2006; Barnea and Rubin, 2010; Krüger, 2015).

However, since the definition of sustainability is still a matter of academic and societal debate, there are efforts in order to consolidate it, like the EU taxonomy for sustainable activities (European Union, 2020). Since the establishment of ESG scores, it took not long for the important insight that the measurement itself is part of the problem and reason for the ongoing academic debate. Studies show that results regarding the effects of ESG on financial performance are mainly data-driven (Dorfleitner et al., 2015; Berg et al., 2022). Another issue alongside the data-driven divergence of ESG ratings is the intentional misrepresentation, known as greenwashing, for which Dorfleitner and Utz (2023) provide a conceptual framework. Later work of Aswani et al. (2024) exemplifies that this is also true for the measurement of carbon emissions and their impact on corporate financial performance. Depending on the third party entity attempting to measure certain aspects of sustainability, prices, performances and derivatives as outcomes differ. One study by Berg et al. (2020) even shows that there is a back-engineering problem, since the maximization of returns still prevails within the financial industry and therefore ratings are re-calibrated ex-post to deliver superior performance.

This dissertation attempts to add a different perspective to ESG. It is not only important how firms differ across the desirable goals within ESG, but also what characterizes and affects companies that exhibit opposing and socially undesirable behaviors, such as corporate scandals. In its focus are the aspects of corporate social irresponsibility (CSI), as an additional perspective or source of complementary information to ESG, and sheds light on these aspects. Following the rationale of the economic theory of crime by Becker (1968), rational employees and corporations could engage in unethical practices under the premise that the associated utility of such an action is higher than the expected value of the punishment. This economic rationale provides a theoretical foundation for the reality of corporate misconduct respectively corporate social irresponsibility. Thanassoulis (2023) delivers an equilibrium framework as to where within a structured economy misconduct can be tolerated. Dumitrescu and Zakriya (2022) show that regarding corporate misconduct and poorly governed firms, there are higher uncertainties in future earnings forecasting power after 2008. Dorfleitner et al. (2022) find that corporate misconduct is influenced by political, cultural, societal, and firm-specific variables. This dissertation is aligned with these important works, in the sense that it is not only important to focus on the societal benefitting aspect of sustainability, but to also analyze the undesired aspects of it. Since corporate social responsibility and corporate social irresponsibility are complementary sides of the same coin, it is valuable to look at the neglected side of this endeavor.

## 1.4 Contribution

Table 1.1 provides an overview of all studies included in this dissertation as well as an assignment to the corresponding chapters, the publication status, and the journal in which the study is published.

Table 1.1: Overview of publications.

| Chapter | Title | Publication | |
|---|---|---|---|
| | | Status | Journal |
| 2 | Real Estate Security Token Offerings and the Secondary Market: Driven by Crypto Hype or Fundamentals? | Published Open Access | Journal of Banking & Finance |
| 3 | German FinTech companies: A market overview and volume estimates | Published Open Access | Credit and Capital Markets |
| 4 | Signaling in the Market for Security Tokens | Published Open Access | Journal of Business Economics |
| 5 | Revealing the Risk Perception of Investors using Machine Learning | Forthcoming Open Access | European Journal of Finance |
| 6 | How socially irresponsible are socially responsible mutual funds? | Published | Finance Research Letters |
| 7 | The Corporate Payout Puzzle: About the Payout Policy between CSI and CSR | Working Paper Under review | European Journal of Finance |
| 8 | The Good left Undone: About future scandals, past returns, and ineffectual ESG | Working Paper Last Review | Journal of Banking & Finance |

This tables provides an overview of the chapters within the dissertation and the publication status as well as the targeted or published journal.

The remainder of this dissertation is organized as follows: The following pages give an executive summary of each study, highlighting the contribution of each chapter, followed by the individual studies as outlined in table 1.1. The dissertation ends with a section on further research approaches and limitations as well as an outlook in section 9.2.

## 1.5 Summary of the Chapters

### Real Estate Security Token Offerings and the Secondary Market: Driven by Crypto Hype or Fundamentals?

The blockchain offers manifold possibilities of making formally illiquid assets fungible. Especially for real estate as an asset class, the fungiblity is a central problem, which is costly and time demanding, involving various entities. Therefore, investing in real estate is limited for private investors either doing it on their own or by mutual funds. The personal investment is problematic, first by the lot size problem meaning that for the regular investor one piece of real estate is associated with a essential proportion of her portfolio, resulting in concentration risks and a lack of diversification. Second, the asset is still illiquid, meaning that selling the piece of real estate is associated with costs and time delay, while the price is more related to negotiation and location than to total supply and demand. Mutual funds on the other hand face similar problems but differently packaged. They need to hold a certain amount of cash, to honor redemption. The selling of a mutual fund is regularly associated with a discount on the net asset values while the real time determination of the portfolio value is nontransparent to investors. One possible solution is proposed by the blockchain in the form of issuance of real estate within security tokens. The tokenization enables the transition of all rights, payments, and responsibilities in the digital realm.

This study analyzes 173 real estate pieces issued on the Ethereum blockchain and the corresponding blockchain transactions of these properties, amounting to over 238,000 transactions from 2019 until December 2021. It answers the question whether the issuance of these real estate tokens is determined rather by the characteristics of the real estate itself, or the surrounding market environment both within the real economy and the crypto ecosystem. Moreover, by the properties of decentralized finance, the paper analyzes how many investors are involved, how much money they invest, how long they hold the tokens and what factors drive them to buy or sell. The tokenization of alternative assets was so far researched in terms of theoretical, legal or technological aspects, but not empirically in terms of economic effects (Gupta et al., 2020; Liu et al., 2020a; Markheim and Berentsen, 2021; Baum, 2021). Besides Swinkels (2023), it is one of the first and most detailed studies, analyzing this new kind of investment and how it functions within traditional financial markets.

It shows that the investment decisions made are by no means just a hype of crypto enthusiasts. Furthermore, investors tend to diversify their portfolios. However, a true diversification across the majority of investors is not yet recognizable, which can also be attributed to the emerging nature of real estate tokenization as well as the comparatively small number of listed projects. Another key contribution of this work is the analysis of all blockchain transactions as well as the netting in the sense of a balance sheet for each individual investor. This allows the attribution of each transaction to a wallet, the determination of transactions as well as the holding periods of the corresponding investments. This component enabled to answer the question, to what degree the investments or capital flows are driven by the property characteristics, the sentiment of the crypto market, and macro-economic factors. The study is published open-access.[1]

### German FinTech companies: A market overview and volume estimates

This study, funded by Deutsche Bundesbank, provides a comprehensive overview of the German FinTech landscape. It identifies the relevant companies within this business segment, based on the previous studies by Dorfleitner et al. (2017). It comprises company attributes like location, founders, founding date, number of employees, legal status, and most importantly an estimation of their market volume.

The hand-collected sample includes 978 companies and their attribution to operating segments according to the taxonomy of Dorfleitner et al. (2016). It explicates a transition from exponential to now linear growth of market volumes across all segments, confirming the maturation from niche to market and underscoring the importance of FinTech firms for science and the German economy.

The value the study provides lies foremost in the identification and observation of this market. Since these companies mainly operate within the digital space and are often associated with well known financial industry players without explicitly interacting with costumers, it is difficult for regulators as well as scientists to get a hand on information about these companies and especially to tell how relevant they are. The hand collected data set as well as the paper is published open-access.[2]

### Signaling in the Market for Security Tokens

Security Token Offerings (STO), the subsequent evolution of unregulated initial coin offerings, are the attempt to bring traditional financial instruments and the positive aspects of regulation to the blockchain. The hand-collected, international sample of 138 STOs as well as 108 security tokens traded on secondary market places is used to analyze which factors contribute to the success of funding within the offering process. Furthermore,

[1] The paper is published as Kreppmeier et al. (2023) and is available through Open Access: https://www.sciencedirect.com/science/article/pii/S0378426623001450.

[2] The study is published as Dorfleitner et al. (2023c) and is available through Open Access: https://elibrary.duncker-humblot.com/article/72485/german-fintech-companies-a-market-overview-and-volume-estimates. The data is also published as Dorfleitner et al. (2023b) and is available through Open Access: https://data.mendeley.com/datasets/438ytjyzxk/3.

the study focuses on drivers of liquidity in secondary markets as well as the financial performance in terms of returns.

The liquidity thereby is measured by the estimators of Amihud (2002), Amihud et al. (2006), and Corwin and Schultz (2012), which are traditionally used for low-frequency markets, but according to Brauneis et al. (2021) they are also the most suitable measures for capturing blockchain-related liquidity. For the determination of returns, the study follows the approaches of Fisch and Momtaz (2020) as well as Momtaz (2021a) by calculating buy-and-hold returns (BHR) and buy-and-hold-abnormal returns (BHAR), where the returns are adjusted for the development of value-weighted benchmarks for different time periods.

Since the market for security tokens is young in comparison to other alternative financing mechanisms, the study observes both extremes regarding returns, indicating that an investment in STOs can lead to exceptional financial gains, but also has the risk of up to a total loss, which often is not reflected in prices. Furthermore, regarding an investment strategy, a naive diversification delivers higher returns than a value-weighted strategy. The study shows that the STO market still lacks liquidity and professionalism regarding the pricing of tokens. However, these findings are in line with the literature where there is the need to find models with more predictive accuracy for the pricing of blockchain-based assets (Liu et al., 2020a).

However, this study sheds light on some specifics within security tokens, namely on the determinants of funding success. The success of these tokens is associated with the ability to transfer on the blockchain, which is not necessarily a concern of issuers. Furthermore, the jurisdiction of the issuance, unlike traditional financial markets, is mainly the Cayman Islands, Luxembourg, Switzerland, and Germany, where there is more blockchain-friendly legislative around security tokens. Finally, it is noteworthy how the issuance is once more connected to traditional financial theories like the signaling theory. The study is published open-access.[3]

### Revealing the Risk Perception of Investors using Machine Learning

Language, and in the written form, text, conveys important information, to which investors react. One of the first studies on stock prices reacting to the sentiment in text was Tetlock (2007). Although this study was done using comments on social media, it raised awareness within financial markets and academia that not only mandatory report statements and financial accounts matter, but also the topics covered and the sentiment of such statements. Within accounting and finance two different approaches emerged. One is the dictionary

[3] The study is published as Kreppmeier and Laschinger (2023) and is available through Open Access: https://link.springer.com/article/10.1007/s11573-023-01175-3.

approach, by assigning points to certain words and counting them. For finance, this was perfected by Loughran and McDonald (2011) and the continuous work on these approaches, for example by Loughran and McDonald (2014).

The second way to quantify written information is by assigning numerical values to topics, which make up a certain percentage of the text. The dominant technique, which has now been used over a decade within accounting and finance is the Latent Dirichlet Analysis (LDA), proposed by Blei et al. (2003), and subsequent improvement of the algorithm, by Blei and Lafferty (2007). These algorithms were later used in order to explain price movements of stocks after the publication of 10-Ks, most prominently shown by Kravet and Muslu (2013).

Roberts et al. (2019) provided a new kind of algorithm, which allowed its users to give meta information to the algorithm, before it assigned the percentage of topics within a given text. This study uses two samples and compares the traditional methods of quantifying topics of 10-Ks and associating the price movement of stocks with topic probabilities. In this study, we provide meta information about the business model of companies, and then estimate topic probabilities within the 10-K reports and compare them to traditional techniques used in accounting and finance. The study finds that the Structural Topic Model by Roberts et al. (2019) provides more meaningful and easier to interpret latencies of language, and the estimated probabilities provide more information in terms of goodness of fit and statistical significance by explaining the volatility movement after the release of a 10-K.[4]

### How socially irresponsible are socially responsible mutual funds?

This study analyzes a sample of US mutual funds and the sustainability of their equity holdings, as measured by ESG scores, and their social responsibility or irresponsibility, measured by the controversy score. The sample spans from 2003 up until 2018 and comprises 422 mutual fund compositions, which are extracted from mutual funds labeled as sustainable and responsible funds.

Following Wimmer (2013), the study calculates, for every fund, the value-weighted ESG score as well as the value-weighted controversy score, ranks them in quartiles and compares the placement in the different quartiles over time. With contingency tables, it is shown that the majority of mutual funds which have a high ESG or a low controversy scores tend to stay in the upper quartile as well as low ESG or high controversy compositions stay in

[4]The paper is accepted and forthcoming in *European Jorunal of Finance* Open Access. A preprint is published as Koelbl et al. (2024) can be found here: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3686492. This paper circulated previously under the working-title: “Can Risks be Good News? Revealing Risk Perception of Real Estate Investors using Machine Learning” as Koelbl et al. (2020) which is documented here: https://europepmc.org/article/ppr/ppr241830.

the bottom quartile. This means for investors who seek to invest in sustainable or socially responsible mutual funds that their initial screening regarding these factors stays persistent over time. Therefore, they do not need allocate their investments differently over time, if they want to keep their sustainability or social investment criteria.

However, the study shows a different problem of mutual funds if ESG and controversies are considered at the same time. Fund compositions with the highest ESG score tend to have the worst controversy score and vice versa. This can probably be attributed to higher awareness of controversial behavior within at least seemingly sustainable firms in terms of ESG scores. Furthermore, it shows the surprising result that mutual funds with higher fees have better controversy scores, but worse ESG scores, which can possibly be attributed to the fact that highly paid fund managers are concerned about their reputation in terms of investing in controversial activities and are also avoiding the down-side risks of these kinds of investment.[5]

### The Corporate Payout Puzzle: About the Payout Policy between CSI and CSR

This study analyzes the corporate payout policy for an international sample of firms comprising 7,260 entities spanning from the year 2002 to 2021. The total payout of a firm, consisting of dividends and share buy-backs, is one of the most important ways for a firm to communicate with its shareholders and at the same time reduce information asymmetries. It is therefore a very important research topic within corporate finance for decades (Lintner, 1956; Miller and Modigliani, 1961). However, due to the importance of the topic and regarding different theories on how and why corporations change their payout policy, it is still a matter of academic debate for corporate finance (Guttman et al., 2010; Deshmukh et al., 2013).

The study highlights that sustainable companies, measured by the ESG score, tend to pay higher dividends than unsustainable ones in the global sample. However, in recent decades firms tend to use stock repurchases as the major form of payout, since there are advantages in the delay of taxation of capital gains as well as an improvement within accounting measures, which is recognized by investors (Jagannathan et al., 2000; Fama and French, 2001; Grullon and Michaely, 2002; Brav et al., 2005; Skinner, 2008). Additionally, while dividends tend to be kept constant, share buybacks represent a reliable and more flexible mechanism for payout, and therefore should convey reliable information for investors. According to the signaling theory, rational decision makers within firms should only buy back shares if they are priced below or equal to their fundamental value (Miller and Rock,

[5] The study is published as Dorfleitner et al. (2021) and is available through: https://www.sciencedirect.com/science/article/pii/S1544612321000714.

1985).

The main contribution of this study, however, is to investigate if corporations use short-term declines of stock prices for share repurchases in the aftermath of corporate social irresponsibility or in other terms corporate scandals. The market timing hypothesis, i.e. well-timed exploitation of diverging beliefs of the market and the management about the true valuation of a firm is a frequently postulated research question within the strand of literature of corporate payout policy (Dittmar and Field, 2015; Ben-Rephael et al., 2014; Ikenberry et al., 2000; Peyer and Vermaelen, 2009). However, the interplay of corporate social irresponsibility and payout policy is so far missing.

The study finds by various statistical models, for example two-stage least square regressions and robustness checks in this international sample, that socially irresponsible companies reduce their total payout and tend to rather cut back their stock repurchasements than their dividends in the aftermath of a corporate scandal. Furthermore, it is shown within a hand-collected and pair-matched sample that companies involved in a scandal take more time to announce their next repurchase of shares. It therefore highlights the importance for investors to consider not only the sustainability of firms, for example in terms of ESG, but also to focus on the component of corporate social irresponsibility for continuous payout in form of dividends and share repurchasements.[6]

### The Good left Undone: About future scandals, past returns, and ineffectual ESG

This study analyzes the performance of companies, in terms of risk-adjusted returns, before and after incidents of corporate social irresponsibility or scandals. It comprises a worldwide sample of 10,500 companies across a time span of 20 years. It shows significant evidence that outperforming firms, measured for example within the framework of Fama and French (2015), have tendencies to be involved in corporate scandals in the future. Considering rational behavior of employees and corporations, even unethical behavior happens in most cases only under the premise that the associated utility of such an action is higher than the expected value of the punishment times the probability of detection Becker (1968).

The study argues, under the assumption of information efficient markets (Fama, 1970), that unethical behavior of firms should be reflected in prices and returns. Neglecting environmental or safety standards, accounting fraud or tax evasion should be in part short-term beneficial, otherwise it would be irrational to pursue such illicit tactics.

To find evidence for this hypothesis, the number of scandals of publicly traded companies is used for roughly 10,500 companies. The data is retrieved from Refinitiv and consists of

[6]The study is published as a preprint as Sparrer and Laschinger (2024) and is available online through: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4666772.

over 30,000 reports of news agencies, financial news providers, legislative cases and so forth. These sources are also employed for the calculation of individual pillars within the ESG score. To test the hypotheses, various statistical models and methods are used, beginning from a panel vector autoregression (PVAR) model detailed by Holtz-Eakin et al. (1988) and Love and Zicchino (2006), to generalized impulse response functions (GIRF) with bootstrapped confidence intervals in accordance with Pesaran and Shin (1998), two-way fixed effects models in the classical sample and within a propensity-score balanced sample, as well as various count data models including corrections for the inflated zero assumptions in the robustness section.

Across the statistical models employed, the study finds consistent and statistically significant evidence that outperformance in terms of risk-adjusted returns is positively associated with future corporate scandals. All models control for the classical ESG score, which also shows a positive connection with corporate scandals in line with the literature. The study contributes therefore that corporate social irresponsibility is another important dimension for investors since outperformance, which cannot be explained by classical factors models, could indicate and predict future corporate scandals. The study's findings suggest that incorporating corporate social irresponsibility as an additional dimension for investors may challenge the efficient market hypothesis, as it implies that information regarding social irresponsibility can provide predictive power beyond what is captured by classical factor models.[7]

[7]The study is published as a preprint as Laschinger and Sparrer (2023) and is available online through: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4186962.

# Chapter 2

# Real Estate Security Token Offerings and the Secondary Market: Driven by Crypto Hype or Fundamentals?

This research project is joint work with Julia Kreppmeier (University of Regensburg), Bertram I. Steininger (KTH Royal Institute of Technology, Stockholm) and Gregor Dorfleitner (University of Regensburg) and has been published as Kreppmeier, J., Laschinger, R., Steininger, B. I., Dorfleitner. G., (2023), Real estate security token offerings and the secondary market: Driven by crypto hype or fundamentals?, *Journal of Banking & Finance*, Volume 154, 106940.

**Abstract** Tokens, the digital form of assets, are an innovation that has the potential to disrupt how to transfer and own financial instruments. We hand-collected data on 173 real estate tokens in the USA between 2019 and 2021 and trace back 238,433 blockchain transactions. We find that tokens provide broad real estate ownership to many small investors through digital fractional ownership and low entry barriers, while investors do not yet hold well-diversified real estate token portfolios. We analyze the determinants of the success of security token offerings (STOs), secondary market trading, and daily aggregated capital flows. In addition to some property-specific determinants, we find that crypto-market-specific determinants, such as transaction costs and the related sentiment, are relevant both to the STO and capital flows.

**Keywords** Digital Asset, Security Token Offering (STO), Real Estate Token, Blockchain, Distributed Ledger Technology (DLT), Decentralized Finance

**JEL** G24, G32, K22, L26, M13

## 2.1 Introduction

Innovation and technology have influenced and enhanced financial services and products for a long time. One of the most important technical innovations in this context is the *Distributed Ledger Technology* (DLT), a decentralized transparent and tamper-proof verification system.[1] Thus, the blockchain transfers the traditionally centralized ledger system using a single book to the digital world. This technology enables the creation and exchange of digital assets in the form of tokens. Tokenization refers to digitally adding and representing assets in the blockchain (Benedetti and Rodríguez-Garnica, 2023; Schär, 2021). Tokens can be endowed with value, rights, and obligations, similar to traditional forms of ownership, such as stocks or funds. *Smart contracts*, which self-execute once pre-specified conditions are met (Buterin, 2013), enable the issuance and the transfer of tokens time- and cost-efficient. Consequently, financial intermediaries such as banks, exchanges, clearing houses, and notaries are rendered obsolete.

Utility and security tokens can be used to tokenize various rights and assets. Utility tokens grant consumption rights linked to platform services and are issued through an initial coin offering (ICO). Security tokens represent shares of ownership in corporate equity, commodities, currencies, or real estate, and they are issued through a security token offering (STO). After ICOs suffered from a lack of investor protection and frequent fraudulent activities (Momtaz et al., 2019), security tokens emerged as innovative and more trustworthy investment products (Lambert et al., 2022). Security tokens are classified as conventional securities and thus subject to the corresponding regulatory requirements. They can be traded on secondary markets after the offering, enabling divestment and liquidity. The concept of fractional ownership by digital tokens facilitates the fragmentation of assets into multiple tokens, attracting new investors globally to gain access to previously lumpy and illiquid asset classes with high entry barriers. Tokenization is particularly suitable for assets such as land and properties due to their high costs, indivisibility, involvement of multiple intermediaries, and high regulatory requirements (Baum, 2021). Tokens entail lower transaction times since clearing and settlement occur instantly, and costs for third parties (e.g., a broker or notary) is much lower (Ante and Fiedler, 2020; Lambert et al., 2022; Yermack, 2017). This development opens up new diversification opportunities for investors while significantly reducing costs and illiquidity premia, paving the way toward entirely digitized financial markets.

The financial industry has already developed various solutions for (in-)direct investments in real estate due to the attractive characteristics of real estate in terms of constant cash flows or low correlation to stocks and bonds. Specifically, open and closed-end funds or

[1] In this article, we employ the terms DLT and blockchain synonymously, even though the blockchain represents only one subtype of DLT. For a detailed discussion, see Liu et al. (2020b).

REITs enable retail investors to gain access to this asset class. The increasing adoption of blockchain has led to the emergence of real estate tokens as a new investment vehicle and digital surrogate for direct property ownership (Baum, 2021). A real estate token, like closed-end funds, mostly comprises one property and not a portfolio of properties, such as open-end funds and REITs. In the case of REITs or funds, investors do not own the properties and, unlike tokens, cannot influence the decision to invest in a particular property. A token gives the investor fractional ownership of the property, making it the technically closest form to fractional direct investment to date. In contrast to closed-end funds, token investors can avoid high minimum investment amounts and administrative costs.

The literature on real estate tokens is to date mainly of a theoretical nature regarding the general procedure (Gupta et al., 2020; Liu et al., 2020a; Markheim and Berentsen, 2021), financial application (Baum, 2021; Markheim and Berentsen, 2021), legal (Konashevych, 2020), and technical aspects (Gupta et al., 2020). Markheim and Berentsen (2021) present descriptive data based on a small sample of real estate tokens, where they point, despite the many theoretical advantages of tokens, towards challenges, such as regulatory uncertainties and relatively long transaction times. Swinkels (2023) examines the liquidity and ownership of real estate tokens using the same data source as our study, albeit with an earlier end date, and considers 58 tokens. His findings suggest that a tokenized property has, in the mean, 254 owners, with ownership changes occurring annually on average. In addition, he concludes that investors are interested in the exposure to the residential house price index, as token prices are linked to housing prices. Our study starts one step earlier and differentiates between the determinants of STOs on the transaction level and daily capital flows on the macro level.

We hand-collected data on 173 real estate tokens with their property and financial characteristics in the USA between 2019 and 2021. Moreover, we examine the related 238,433 blockchain transactions to analyze investor behavior. We have enriched this database with crypto market-specific characteristics and macroeconomic indicators. In this regard, our main findings are threefold.

First, we are among the first to trace back the underlying blockchain transactions in an empirical analysis to derive insights into investor behavior. Our analysis shows that investors hold an average of ten different tokens and an investment amount of 4,030 USD, which does not represent a well-diversified real estate token portfolio. Tokenization provides broad access to real estate ownership for many small investors as property ownership is not concentrated on a few large investors. Most investors acquire tokens during STOs, while secondary market trading plays a minor role. Second, we investigate the determinants of STO success, defined as the number of days until all tokens are sold and the mean funding amount per day. For the latter and primary success variable of interest in this study, we find that some property-specific fundamentals and the crypto market-related transaction costs explain most of the success of the STO. Third, we switch from the individual STO to the macro-level view of aggregated daily capital flows per property to account for the specific crypto market over time. We observe that real estate token investors similarly consider the crypto market sentiment and transaction costs when purchasing tokens. In contrast, only transaction costs directly reducing the return on investment are relevant when selling. Additionally, macroeconomic factors have a minor role in capital flows.

Our study contributes to several streams of literature. First, we add to the literature on blockchain technology and the economics of digital assets. The first wave of academic literature in this sub-stream focused on ICOs as an innovative form of crowdfunding, bearing the advantage that the blockchain tokens enable secondary market trading (Lee et al., 2022). Empirical studies on ICOs examine success determinants (Fisch, 2019; Howell et al., 2020), investor characteristics and motives (Fisch et al., 2021; Fahlenbrach and Frattaroli, 2021), white papers (Florysiak and Schandlbauer, 2022; Thewissen et al., 2022), and post-ICO performance (Benedetti and Kostovetsky, 2021; Fisch and Momtaz, 2020; Lyandres et al., 2022). Momtaz (2023) emphasizes that the reasons security tokens are driving digitization in finance are interoperability, fractional ownership, instantaneous settlement, and market liquidity. Gan et al. (2021) find that STOs, in contrast to ICOs, entail lower agency costs, lower token turnover, lower cash diversion, and raise higher amounts of funds and firm profits. The existing empirical literature on STOs primarily examines success determinants during the funding process, focusing on the issuer and offering characteristics (Lambert et al., 2022; Ante and Fiedler, 2020).

Second, we contribute to the literature on real estate investments. The real estate sector is a major sector for study in its own right in the literature on crowdfunding (Jiang et al., 2020; Schweizer and Zhou, 2017; Shahrokhi and Parhizgari, 2020). Fisch et al. (2022) compare ICOs and, among others, REITs to analyze whether gender, ethnicity, and geography influence the decision for an ICO. While the authors point out that real estate is a highly relevant use case for blockchain-based financing, they do not directly examine real estate STOs. In a sample of 1,125 ICOs for external firm financing, Howell et al. (2020) find a positive relationship between ICO success, measured by employment, and the operating sector of tokenizing real assets. They attribute this result to the underlying concept of security tokens but do not deepen the analysis further on this aspect. STOs of real estate projects need to be studied separately to simultaneously consider the underlying asset class and the specific crypto market environment.

Third, we complement the literature on portfolio construction and diversification. Diversification is a fundamental concept in portfolio theory (Markowitz, 1952). Goetzmann and Kumar (2008) document that 60,000 individual US investors hold under-diversified equity portfolios, leading to high idiosyncratic risk and, consequently, a welfare loss. The small investment amount resulting from fractional ownership of digital tokens theoretically makes diversification easier. Therefore, we aim to verify whether real estate tokens live up to their promise of portfolio diversification.

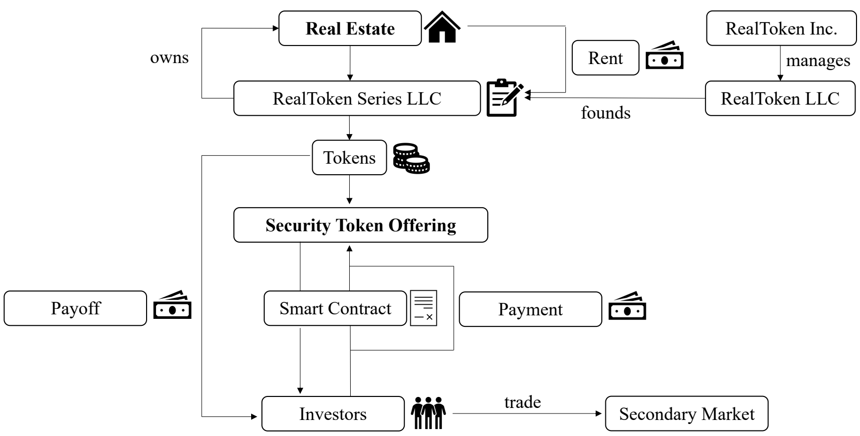
The remainder of this paper is organized as follows. In Section 2.2, we present the real estate tokenization process and derive our hypotheses. We describe our data and method in Section 2.3. The main analyses and discussion of our empirical results are presented in Section 2.4, followed by further analyses and robustness checks in Section 2.5. In Section 2.6, we conclude our study.

## 2.2 Conceptual framework and derivation of hypotheses

### 2.2.1 Real estate tokenization

Our dataset comprises real estate tokens issued by the platform RealToken (RealT), an active issuer and platform for real estate tokens in the USA. Based on the *Howey test*, digital assets are investment contracts and, therefore, considered securities. Consequently, real estate tokens must be registered with the Securities and Exchange Commission and are subject to laws and regulations protecting investors. RealT offers the tokens in unregistered securities offerings, or private placements, under Regulation D 506(c) (US-accredited investors) and Regulation S (non-US investors) of the Securities Act. We illustrate the process of real estate tokenization and STOs in the case of RealT in Figure 2.1 and describe the process below.[2]

Figure 2.1: Process Map




*Note:* This figure illustrates the process of real estate tokenization and STOs in the case of the platform RealT.

[2]For a description of the ICO or STO process, see Momtaz (2020) and Lambert et al. (2022).

RealToken LLC creates a RealToken Series LLC for each property since properties cannot be directly digitalized. This LLC acts as a special purpose vehicle (SPV) and holds the property deed.[3] These SPVs stand solely and legally on their own and are, in the next step, tokenized using the technical standard of the Ethereum ERC-20 token. The properties are primarily rented residential buildings. Property management is outsourced to local professionals. Investors can purchase the tokens during the STO. After successful payment and signing the offering memorandum digitally, they automatically receive the tokens in their wallets employing a smart contract. On the Ethereum blockchain, computing power is required to perform operations successfully, and users have to additionally pay a so-called *gas fee*. The tokens give the investor a deed in the respective tokenized RealToken Series LLC. After operating costs, insurance, and real estate taxes, the net rent is submitted weekly to the RealToken rent contract linked to the property and automatically issued to the token holders' wallets. The value of a token is specified by the assessed property value after a maintenance and repair reserve divided by the total number of tokens issued. RealT charges a fee of 10%, for which investors, in exchange, receive governance tokens from RealT itself. Afterward, the security tokens can be either returned to RealT or traded on decentralized exchanges (DEX) as a means of decentralized finance.[4] The properties are re-valued annually, resulting in the depreciation or appreciation of the tokens. After the rapid increase in transaction costs in combination with longer execution times on the Ethereum blockchain at the beginning of 2021, RealT decided to alternatively enable transactions on the Gnosis blockchain.[5] In particular, for the relatively low weekly rent payments, using Gnosis and avoiding high transaction costs on the Ethereum blockchain is favorable. After elucidating the mechanics of real estate tokenization, the following hypotheses are derived from the academic literature.

### 2.2.2 Derivation of hypotheses

We first tackle the impact of different property-specific factors on the perceived quality, risk, and expected cash flow, which can be related to the success of an offering. From a theoretical perspective, property type and location are the major property-specific characteristics that influence value. These factors are empirically confirmed by various studies (see, e.g., Cronqvist et al., 2001; Pai and Geltner, 2007; Ro and Ziobrowski, 2012; Hartzell et al., 2014). Real estate is naturally immobile, which means that the location determines its value to a large extent. Therefore, a purchaser acquires both the building and the site at

[3]A form to digitize ownership is non-fungible tokens (NFTs) or with the help of Decentralized Autonomous Organizations (DAOs). However, these are only theoretical concepts not often applied to the real estate market and, consequently, lie beyond the scope of this paper.

[4]For a detailed discussion, see Aspris et al. (2021).

[5]Gnosis (formerly xDai) blockchain is a second-layer protocol to create, trade, and hold digital assets on Ethereum.

the same time (Kiel and Zabel, 2008). The options for determining the location's quality are manifold: political or historical zones, indirect factors, such as the school quality of the district, or the distance to important places, such as the central business district. These indicator variables mostly imply indirect influences on house values since investors consider specific locations or location characteristics more or less favorable. In particular, the low minimum investment amount for tokens enables investors to diversify their portfolios more broadly, especially regarding location. This makes the location an important factor for the attractiveness of the STO for an investor and could, consequently, influence the success of a real estate STO.

The size of the property measured by its value determines the rent and return, similar to the way the size factor determines the return on the stock market (Fama and French, 1993). Geltner et al. (2014) report that size is a suitable factor for explaining the return variation of real estate on a large scale. Pai and Geltner (2007) use the market value as a size factor and find the opposite impact compared to the stock market – larger properties have a higher expected return premium. Esrig et al. (2011) state that large properties outperform other properties on an absolute and risk-adjusted basis for different property types. Sirmans et al. (2005) conduct a review of around 125 studies using hedonic modeling to estimate house prices and report that lot size had a positive effect in the vast majority of observations. Therefore, we expect that the size has a positive relationship with the success of the STO.

If the quality of the property is not specified, its age can be used as a proxy for it. A lower quality induces higher uncertainty for maintenance and repair costs and, thus, higher risk for the buyer (Bourassa et al., 2009). Since investors try to avoid this kind of risk, older properties may be less attractive to investors. This argumentation is supported by Sirmans et al. (2005), who find in their review that the influence of age on house prices was almost entirely negative.

The major risk regarding the expected cash flow is a rent default. This risk can be reduced by splitting the rent between several different tenants. Therefore, single-tenant buildings limit the diversification possibilities of potential investors in contrast to multi-tenant properties. The limited diversification options make single-tenant properties, in contrast to multi-tenant properties, less attractive, which may result in a less successful funding process. Opposed to that Ling and Archer (2021) find that single-family properties have a lower risk than multi-family homes because single-family homes are typically located in desirable suburban areas with steady demand. Based on the importance of both effects – lower default risk for multi-tenant buildings vs. location – an exact expectation cannot be formulated, and the issue has to be settled empirically.

In the USA, low-income households can receive rental housing assistance via Section 8 of the United States Housing Act of 1937 (42 U.S.C. §1437 et seq.). This program helps them in finding a decent and affordable place to live. The state pays the rent directly to the landlord, which significantly reduces the risk of payment issues or default. The Section 8 program guarantees token purchasers a stable and predictable rent payment. Consequently, investing in such properties bears a lower risk of rent default. Investors may find properties with a greater percentage of rental assistance from the Section 8 program to be more attractive. As such, our Hypothesis 1 reads:

> **Hypothesis 1:** *The quality of a location, the size of a property, and a higher portion of rental assistance through Section 8 are positively related to the success of an STO, while age is negatively related.*

In addition to the property and financial characteristics, we also consider campaign features commonly known from the literature on crowdfunding (CF) (Belleflamme et al., 2014). In the context of CF, it is decisive for the funding success of a campaign to be able to signal the quality of a project to potential investors (Ahlers et al., 2015). Conventional CF campaigns often have a short or missing track record or lack a market-ready product. Therefore, investors need to base their decision on other information, such as the description in text and pictures on the platforms. This information allows companies to reduce information asymmetries and signal project quality (Diamond, 1984). Apart from the text, pictures assist in visualization and enable an evaluation of the property's location and actual condition. Previous CF studies identified a detailed project description to overcome information asymmetries and increase campaign success (De Crescenzo et al., 2020; Gao et al., 2022). This effect has also been investigated in the literature on real estate for its impact on home prices and home-buyer attention in a similar vein (Luchtenberg et al., 2019; Nowak and Smith, 2016; Seiler et al., 2012). The more detailed and larger the number of pictures, the more realistic and accurate the presentation of the potential investment is for an investor. High-quality projects are incentivized to deploy detailed project descriptions, whereas low-quality projects tend to be vaguer in their disclosures. Therefore, we assume that a detailed project description is a positive quality signal for an investor, which prompts an investment and can increase the success of an offering.

> **Hypothesis 2:** *A detailed project description is positively related to the success of an STO.*

The investment decision process, akin to other markets, is potentially driven by the market-specific environment and investor or market sentiment. Investors follow investment recommendations and central strategies, and retail investors mostly exhibit herding behavior, often caused by market sentiment. Herding behavior has been studied in the traditional stock market (Chang et al., 2000; Chiang and Zheng, 2010; Litimi et al., 2016) and in the cryptocurrency market (Ajaz and Kumar, 2018; Bouri et al., 2019). Investors, particularly non-rational investors like many crypto investors, are potentially subject to herding behavior. Investor sentiment can be particularly pronounced in the market for tokens (Drobetz et al., 2019), as this seems to be in such highly subjective asset classes (Baker and Wurgler, 2006). From an investor perspective, we assume, similarly to Ante and Fiedler (2020), that in the market for STOs, a house money effect exists, meaning that investors take higher risks after prior gains (Thaler and Johnson, 1990), especially during periods of positive market sentiment. Since issuers anticipate this irrational investor behavior, they will await the right time on the market to place the offers. For example, Drobetz et al. (2019) show that companies seeking funding via ICOs avoid phases of general negative market sentiment for their exchange listing, which results in short-term negative returns of the tokens. Token platform operators can time the publication of a project to periods of positive market sentiment. Thus we expect a positive link between market sentiment and the success and daily capital inflows as token purchases and a negative link with daily capital outflows as token sales.

With regard to the specific market environment for blockchain-based tokens, a cost effect that runs counter to the market sentiment must also be taken into account. Apart from the administrative fees directly imposed by the token issuer, specific transaction costs called *gas fees* are additional costs associated with a token investment that need to be considered and paid by the investor. Since gas is needed to perform operations and space is limited on a block, the resulting transaction costs may vary due to fluctuations in supply and demand on the network.[6] Gas fees rise when demand increases, and vice versa; hence, they signify crypto popularity. Additionally, users can pay an extra fee to increase the likelihood of their transaction being included in the next block when demand is high. Gas fees can be observed and predicted easily for investors on corresponding websites opening up the possibility to time the investment and avoid high transaction costs. Momtaz et al. (2022) provide the first empirical evidence of tokens on the Ethereum blockchain, including stablecoins, startup tokens, and lottery tokens. The authors find that investors reduce their trading activity when transaction costs are high. In conclusion, we expect that crypto market transaction costs are negatively related to the success of an STO and capital inflows and outflows because investors seek to circumvent high transaction costs. The decision of an investor to make a real estate token investment can therefore be based on two opposing effects as indicators of crypto popularity, which is why an empirical investigation is required.

> **Hypothesis 3a:** *Crypto market sentiment is positively related to capital inflows, while it is negatively related to capital outflows.*

[6] By definition, 'gas fee' and 'transaction fee' are not synonyms, as the actual total cost per transaction is the multiplication of gas used and a base gas fee. For more detailed information on the mechanism and calculation of gas fees, see Ethereum.org (2022).

**Hypothesis 3b:** *Crypto-market related transaction costs are negatively related to the success of an STO as well as capital inflows and outflows.*

## 2.3 Data and method

### 2.3.1 Data sources

We collect the US real estate token data directly from the RealToken platform, resulting in 173 financed projects as of December 31, 2021. The data comprises information at the property level and its financial characteristics. The blockchain transaction data comes from two blockchain explorer and analytic platforms, namely *Blockscout* and *Etherscan*, which was also used by Lyandres et al. (2022). We rely on these two sources for the transaction data as RealT has enabled transactions on the Gnosis blockchain since the beginning of 2021.

### 2.3.2 Method: blockchain transaction analysis

The blockchain is a digital ledger in which one entry corresponds to one transaction. We derive all blockchain transactions related to the real estate tokens in our sample until the end of our observation period in December 2021. The structure of a blockchain transaction comprises the respective token, a unique transaction hash (transaction ID), a time stamp, the number of tokens, and the sending (from) and receiving addresses (to). We trace back investors through their unique and pseudonymous *wallet* address, which is comparable to the account number in the traditional banking sector. Even if an investor can have several wallets and, thus, more than one unique wallet address, we assume that most investors have only one wallet.[7] The switch of the blockchain from Ethereum to Gnosis is no issue regarding the unique wallet address, as Gnosis is built upon Ethereum and, therefore, the wallet addresses remain the same. Due to the focus of our study, we do not consider other investments by investors in their wallets besides real estate tokens. We can clearly distinguish transactions from the STO from secondary market transactions by identifying the emitting wallet address of the platform operator from which tokens are transferred to investors for each property. Consequently, the remaining transactions from non-emitting wallets are secondary market buy-or-sell transactions.

Based on the transaction data, we derive several variables that shed light on both investors and their investment strategies concerning tokenized properties. To this end, we analyze

[7] This assumption can be justified for several reasons. On the RealT platform, a user can only deposit one wallet at a time. Swinkels (2023) has submitted a request to the platform operator confirming the assumption. From an academic point of view, Fahlenbrach and Frattaroli (2021) have conducted tests in an ICO sample and found similar results.

two distinct perspectives: the wallet-investor and the token-property perspective. In the wallet-investor perspective, the variable *Properties per Investor* accounts for the number of properties an investor has invested in. This variable addresses the extent to which investors diversify their real estate token portfolio. Further, we convert the number of tokens observed in the transactions into a more easily interpretable and meaningful dollar amount, using the price of the tokens from the STO and calculate the *Holdings per Investor as of Dec 2021* in dollars. To measure the time dimension of the investments and thus the willingness to speculate on the side of the investors, we analyze the *Holding Period all Investors as of Dec 2021* in days. From the token-property perspective, we consider the concentration of ownership with the Herfindahl-Hirschman index (Herfindahl, 1950; Hirschman, 1964). We calculate the Herfindahl-Hirschman index as

$$HHI = \sum_{i=1}^{N} s_i^2 \tag{2.1}$$

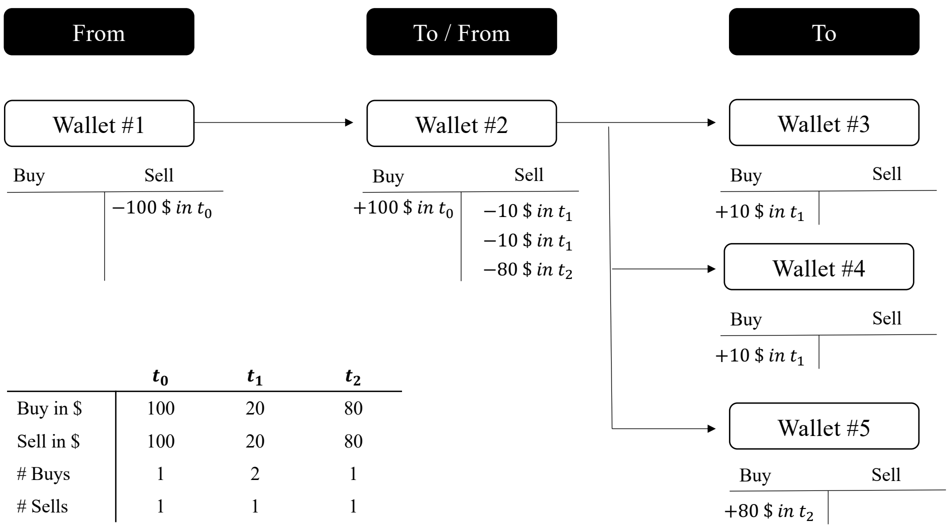
in which $s$ is the percentage of ownership of an investor $i$, and $N$ constitutes the total number of investors on the property level. The index ranges between $1/N$ and 1. The latter implies that complete ownership is concentrated on a single investor. To account for variations in the $HHI$ caused by a different number of investors in the properties and to facilitate direct comparison between properties, we consider the normalized Herfindahl-Hirschman index as

$$HHI^* = \frac{HHI - 1/N}{1 - 1/N}. \tag{2.2}$$

This measure varies between 0, which corresponds to equal ownership of all investors, and 1, which corresponds to a single investor with full ownership. The variable *Investors per Property* measures the number of unique wallets invested in a specific property.

In addition, we examine investors' trading activities on both the buy and sell sides. With the variable *STO Buy*, we measure the absolute dollar amount of purchases during the STO. Figure 2.2 in the Appendix illustrates the calculation scheme of the *Secondary Market Buy* and the *Secondary Market Sell* side. We implemented a daily balance calculation to summarize the transactions per day to determine the daily dollar holdings per wallet. This approach entails evaluating the changes in wallet balances over time, where an increase in the balance indicates a buy transaction, and a decrease in the balance represents a sell transaction. We use this method because the dollar volume per wallet gives more insight than the volume per individual transaction. Therefore, *Secondary Market Buy* depicts how large the purchasing investment amounts are in the secondary market. The variable *Secondary Market Buy/Existing Exposure* indicates the percentage of purchases on the secondary market compared to the existing investment. On the sell side, we analyze with the variable *Secondary Market Sell* the dollar amount investors sell on the secondary market. The variable *Secondary Market Sell/Existing Exposure* puts this in relation to the existing investment. Lastly, the variable *Holding Period Sellers* measures how many days investors who sell their tokens have previously held them. The latter two variables provide insights into whether investors are interested in regular cash flows from the rent payments or the changes in the token's value itself.

Figure 2.2: Blockchain Analysis Scheme




*Note:* This Figure illustrates the calculation scheme for determining the buy and sell sides in Table 2.2. We used a daily balance calculation for each wallet to evaluate changes over time. An increase in balance represents a buy transaction, while a decrease indicates a sell transaction.

### 2.3.3 Method: multivariate analysis STO success determinants

In the first multivariate analysis, we test for determinants of the success of real estate STOs. We operationalize the funding time and speed as our measures of success. The funding time measures the number of days until 95% of the tokens have been transferred to the investors' wallets since RealT retains tokens to ensure liquidity in the secondary market, based on the blockchain transaction data.[8] Therefore, it is a proxy for the pure time dimension of success. We consider a project more successful if it takes less time to secure funding. We sub-categorize the funding time into the *Funding Time until Success* for the sub-sample of successfully funded projects transferred to the investors' wallets. As the second sub-category of funding time, we simultaneously examine successful and unsuccessful projects regarding the *Funding Time until Dec 2021* to obtain a sample free of survivorship bias. We estimate the parametric accelerated failure-time (AFT) survival model to account for unsuccessful projects correctly and because the proportional hazards

[8] In Subsection 2.5.1, we vary and verify the 95% assumption for an STO in order for it to be considered successful.

assumption is violated for the semi-parametric Cox model. We apply the lognormal and log-logistic distributions since both present the most appropriate statistical fit for the distribution of our dependent variable. The AFT model is an alternative to modeling survival times often used in crowdfunding (Jiang et al., 2020; Felipe et al., 2022).

The funding time may be positively related to higher amounts of *Total Investment*. Therefore, we alternatively consider the measure speed. It is the fraction of 95% of the *Total Investment* to the funding time. Thus speed measures the mean investment amount funded per day.[9] Successful projects have a higher speed, corresponding to a higher daily funding amount. Analogously to the analysis of the funding time, we sub-categorize speed in the first specification with the corresponding *Funding Time until Success* into the dependent variable *Speed until Success* for successful projects. In the second model specification, we examine all projects as of December 2021 with *Speed until Dec 2021*. For projects that have not been successfully funded until the end of our observation period and are on the market longer than the mean time of *Funding Time until Success*, we equate *Speed until Dec 2021* to 0 to proxy a low speed and prevent distortions from unsuccessful projects with a large *Total Investment*. For projects that have not been successfully funded until the end of the observation period and are on the market shorter than the mean time of *Funding Time until Success*, we use the actual amount of money raised instead of *Total Investment*.

In the baseline regression, we include the financial, property, and campaign variables which we expand in the second specification with crypto market-specific characteristics. We use robust standard errors that are one-way-clustered in all regressions and quarter-year dummy variables. The financial characteristics of the property include *Rent per Token p.a.* for the annual rent a token holder receives per token. The variables *Expected Yield* and *Total Investment* are data publicly available before funding. These variables are determined by the property characteristics and thus can be indirectly influenced by the token issuer. The financial ratio *Expected Yield* is given by the ratio of the net rent to the token price. *Total Investment* refers to the amount of money needed to secure successful funding. This variable is commonly used in the CF (Block et al., 2018; Mollick, 2014), ICO (Adhami et al., 2018; Fisch, 2019), and STO literature (Ante and Fiedler, 2020; Lambert et al., 2022) to determine project success and represents the funding amount actually collected. However, due to the technical procedure on the blockchain, the *Total Investment* in our context is always entirely issued as part of tokenization but not necessarily fully transferred to investors. At the same time, the issuer keeps the remaining tokens. Therefore, we do not apply this variable as a measure of success.

The property characteristics comprise the variables *Age*, *Lot Size*, *Section 8* as the percentage of the share of financially supported housing within one property, and the type of use

[9] This definition is analogous to the average velocity in physics, based on the investment amount instead of distance.

with the dummy variable *Single Family* if one family is the only tenant. For a suitable location variable, we rely on the dummy variable *Detroit* and the metric variable *Distance DTWN* to account for location quality since these variables are easily accessible and straightforward to understand for a retail investor. Similar to Swinkels (2023), we assume that rental properties outside of Detroit are more attractive for investors for diversification reasons, as the majority are located in Detroit. In addition, we also measure the distance to downtown in miles with the variable *Distance DTWN* to incorporate the micro-effects of the location. The campaign characteristics related to the literature on crowdfunding include the number of pictures with the variable *#Pictures* and the length of the descriptive text with *#Characters* for the particular property project.

For market-specific variables, we include for the crypto environment the variable *Gas Fees* for transaction costs on the Ethereum blockchain, converted to USD. Additionally, we include the S&P Case-Shiller Home Price Index with the variable *Housing Market* for the respective regions corresponding to the particular cities where the properties in our sample are located (Detroit, Chicago, Cleveland, New York, and Florida), lagged for one month. Since investors participate in the value depreciation or appreciation of the property with the value of their token, they care about the growth potential of the real estate market. They may be more willing to purchase a token if the regional real estate market grows. All variables are defined in Table A.1 in the Appendix.

### 2.3.4 Method: multivariate analysis funding determinants

With the multivariate analysis of STO success determinants, we analyze the STO at that specific point in time. However, when considering the crypto market over time, we must detach from mostly time-invariant STO characteristics and move on to the macro-level view of real estate token market activity. Hence, we can additionally account for daily fluctuations, notably for short-term particularities and shocks. In concrete terms, this shifts our models from the STO perspective to a daily view of capital inflows and outflows over time. To account for unobserved effects regarding individual characteristics and time, we employ a two-way fixed effects panel regression to analyze the determinants of daily inflows and outflows per property.

The dependent variables, daily *Inflow* and *Outflow* per property, are calculated based on the blockchain transaction data. *Inflow* indicates how much money investors spent during the STO or on the secondary market per property on a given day. *Outflow* measures which amount of money the investors sold from a property on the secondary market on a given day.[10] The *Inflows* and *Outflows* in the market for real estate tokens may be

[10] *Inflows* are the aggregated *STO Buy* and *Secondary Market Buy* and *Outflow* is *Secondary Market Sell* per project, reported in Table 2.2. The difference in the number of observations is due to the fact that there were no sales on some days. The difference in the mean is caused by *STO Buy* transactions and

influenced by determinants and shocks both in the crypto market and the macroeconomy. Therefore, to account for the peculiarities of the crypto market, we consider from the sentiment perspective the five-day cumulative return of the native token of the Ethereum blockchain, Ether (ETH), with the variable *ETH Price* denominated in USD. The market capitalization of ETH is the second largest after Bitcoin on the cryptocurrency market as of December 31, 2021, and Ethereum is the primary platform for security tokens. Since the cryptocurrency market is still in its infancy and the general conditions are changing, it is characterized by high volatility. To incorporate short-term shocks in the crypto market, we include the dummy variables *ETH Shock* and *Gas Shock*. *ETH Shock* equals one if the cumulative return of five days prior to the observation decreased by more than 5% and *Gas Shock* which equals one if the cumulative return of *Gas Fees* increased by more than 5% in five days. For the macroeconomic environment, we include the *One-month Treasury*, *Ten-year Treasury*, and the *Aruoba-Diebold-Scotti* Business Conditions Index (*ADS Index*) of Aruoba et al. (2009). According to the Federal Reserve Bank of Philadelphia, the *ADS Index* covers seasonally adjusted macroeconomic indicators, including, among others, initial jobless claims (weekly), payroll employment (monthly), industrial production (monthly), and real GDP (quarterly). The index offers the advantage that, unlike, e.g., GDP or the unemployment rate, the data is provided daily, corresponding to the daily frequency of our dependent variables. Due to its high frequency, the index is increasingly used in academic research (see, e.g., Caporin et al., 2022; Da et al., 2014).

### 2.3.5 Descriptive statistics

The descriptive statistics for analyzing success determinants are displayed in Table 2.1 in Panel A. In our total sample of 173 real estate STOs, 72% were successful, which indicates that 95% of the tokens were transferred to investors. The sub-sample of successful STOs has a mean *Funding Time until Success* of 48.72 days and a median value of 26.92 days. In contrast, the *Funding Time until Dec 2021* for the entire sample is correspondingly longer, with 73.01 days in the mean. The minimum of 2.63 indicates that some very attractive projects sell off quickly. The money-oriented variable *Speed until Success* has a mean of 10,550 USD/day for successful projects and a median of 4,190 USD/day. When considering successful and unsuccessful projects regarding the *Speed until Dec 2021*, the mean of 8,300 USD/day is subsequently lower. The minimum *Speed until Dec 2021* of 0 represents projects not fully funded within the mean of *Funding Time until Success* of 48.72 days.

For the *Expected Yield*, the mean is at 11%. The mean property value measured by the highly skewed *Total Investment* at 168,020 with a median of 66,500 shows that most

represents the capital that investors actively hold in tokens.

Table 2.1: Descriptive Statistics

| | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Variables for STO success determinants** | | | | | | | | |
| **Dependent variables** | | | | | | | | |
| Funding Success | 173 | 0.72 | 0.45 | 0 | 0 | 1 | 1 | 1 |
| Funding Time until Success | 125 | 48.72 | 49.53 | 2.63 | 9.87 | 26.92 | 82.29 | 226.70 |
| Funding Time until Dec 2021 | 173 | 73.01 | 67.03 | 2.63 | 11.91 | 56.53 | 121.00 | 323.00 |
| Speed until Success | 125 | 10.55 | 20.38 | 0.27 | 0.95 | 4.19 | 9.22 | 128.48 |
| Speed until Dec 2021 | 173 | 8.30 | 18.45 | 0.00 | 0.27 | 1.78 | 8.64 | 128.48 |
| **Explanatory variables** | | | | | | | | |
| Rent per Token p.a. | 173 | 5.98 | 1.59 | 3.96 | 5.53 | 5.81 | 6.08 | 21.82 |
| Total Investment | 173 | 168.02 | 205.54 | 48.08 | 60.58 | 66.50 | 144.45 | 985.91 |
| Expected Yield | 173 | 0.11 | 0.01 | 0.07 | 0.11 | 0.11 | 0.12 | 0.13 |
| Age | 171 | 85.02 | 18.48 | 2 | 74 | 84 | 94.5 | 134 |
| Lot Size | 166 | 5,338.20 | 2,951.67 | 871 | 3,920 | 4,792 | 5,644.5 | 29,620 |
| Section 8 | 173 | 0.18 | 0.37 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Single Family | 173 | 0.64 | 0.48 | 0 | 0 | 1 | 1 | 1 |
| Distance DTWN | 173 | 4.70 | 1.73 | 1.08 | 3.61 | 4.51 | 5.40 | 9.63 |
| Detroit | 173 | 0.80 | 0.40 | 0 | 1 | 1 | 1 | 1 |
| #Pictures | 173 | 4.34 | 4.77 | 1 | 2 | 3 | 5 | 35 |
| #Characters | 172 | 205.65 | 305.82 | 0 | 0 | 0 | 364.2 | 1,654 |
| Gas Fees | 173 | 6.68 | 4.53 | 1.11 | 1.78 | 6.79 | 9.42 | 16.85 |
| Housing Market | 173 | 150.67 | 24.35 | 127.56 | 139.63 | 148.45 | 155.38 | 343.64 |
| **Panel B: Variables for funding determinants** | | | | | | | | |
| **Dependent variables** | | | | | | | | |
| Inflow | 26,940 | 1,189.39 | 11,201.43 | 0.00 | 5.00 | 16.01 | 117.98 | 493,278.80 |
| Outflow | 26,016 | 218.44 | 1,484.38 | 0.00 | 4.87 | 13.80 | 65.50 | 71,819.98 |
| **Explanatory variables** | | | | | | | | |
| Gas Fees | 654 | 4.37 | 4.23 | 0.76 | 1.41 | 1.78 | 8.11 | 18.00 |
| ETH Price | 654 | 1,266.96 | 1,392.49 | 110.61 | 202.23 | 387.98 | 2,232.96 | 4,812.09 |
| Gas Shock | 654 | 0.38 | 0.49 | 0 | 0 | 0 | 1 | 1 |
| ETH Shock | 654 | 0.30 | 0.46 | 0 | 0 | 0 | 1 | 1 |
| One-month Treasury | 627 | 0.53 | 0.77 | 0.00 | 0.05 | 0.09 | 1.52 | 2.26 |
| Ten-year Treasury | 627 | 1.29 | 0.44 | 0.52 | 0.84 | 1.43 | 1.63 | 2.13 |
| ADS Index | 654 | −0.47 | 5.64 | −26.33 | −0.31 | 0.18 | 0.86 | 8.99 |

*Note:* This table reports the descriptive statistics (number of observations, mean, standard deviation, minimum, $25^{\text{th}}$ percentile, median, $75^{\text{th}}$ percentile, and maximum) for the full sample. For the analysis of STO success determinants, the number of observations of 125 of *Funding Time until Success* and *Speed until Success* refers to the successful projects in the sample; the remaining variables represent the entire sample of 173 observations. For the analysis of the funding determinants, the number of observations differs between *One-month Treasury*, *Ten-year Treasury*, and the remaining explanatory variables, as these data are not provided on bank holidays. All variables are defined in Table A.1 in the Appendix.

properties have a relatively low value. Among the housing characteristics, we observe that 80% of the properties are located in *Detroit* and 64% are *Single Family*. The campaign variables show that the offers, on average, are illustrated with four pictures and described in 205.65 characters. We do not consider the variable *#Characters* further in our multivariate analysis since the median value is zero because the platform did not provide any descriptive text at the beginning. The *Gas Fees* at the day of the STO range from a minimum of 1.11 to a maximum of 16.85, with a mean of 6.68, highlighting that blockchain-related transaction costs fluctuate and can be of crucial interest to token investors.

Panel B presents the descriptive statistics for the analysis of funding determinants. The unbalanced panel data set consists of 26,940 daily *Inflow* and 26,016 daily *Outflow* observations per property per day over our observation period of about two and a half years as of December 2021. On average, *Inflows* have a mean of 1,189.39, highly distorted by the maximum of 493,278.90 from an expensive and quickly sold property. The daily *Outflows* per property amount to a mean of 218.44. The medians of daily *Inflows* and *Outflows* are in a similar magnitude range at 16.01 and 13.80. The daily *Gas Fees* range between a minimum of 0.76 and a maximum of 18.00 throughout the observation period. The mean of *ETH Price* is 1,266.96 with a median of 387.98. The latter two variables illustrate the high volatility of the crypto market, which is why an additional examination of short-term shocks is required. A *Gas shock* is present in 38% and a *ETH Shock* in 30% of the daily observations. Table A.2 in the Appendix displays the Bravais-Pearson correlation coefficients for all of the variables we consider in the analysis of STO determinants. The correlation coefficients between the explanatory variables are moderate and provide initial evidence for our hypotheses.

## 2.4 Main analyses

### 2.4.1 Analysis of blockchain transaction

Table 2.2: Blockchain Transaction Analysis.

| | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Wallet-Investor perspective** | | | | | | | | |
| Properties per Investor | 6,806 | 10.2 | 20.7 | 1 | 1 | 3 | 9 | 171 |
| Holdings per Investor as of Dec 2021 | 6,544 | 4,029.35 | 32,319.99 | 0.00 | 57.96 | 259.45 | 1,398.34 | 1,439,474.00 |
| Holding Period all Investors as of Dec 2021 | 165,161 | 244.51 | 160.59 | 0 | 133 | 221 | 286 | 850 |
| **Panel B: Token-Property perspective** | | | | | | | | |
| HHI* STO | 173 | 0.03 | 0.06 | 0.01 | 0.01 | 0.02 | 0.04 | 0.68 |
| HHI* as of Dec 2021 | 172 | 0.03 | 0.04 | 0.01 | 0.01 | 0.02 | 0.04 | 0.28 |
| Investors per Property | 173 | 401.2 | 201.2 | 31 | 258 | 328 | 501 | 1,173 |
| **Panel C: Buy side** | | | | | | | | |
| STO Buy | 87,048 | 317.82 | 2,467.28 | 0.00 | 35.98 | 57.96 | 162.60 | 155,010.00 |
| Secondary Market Buy | 35,351 | 88.70 | 721.13 | 0.00 | 2.92 | 6.72 | 25.43 | 58,462.74 |
| Secondary Market Buy/Existing Exposure | 35,351 | 0.38 | 11.67 | 0.00 | 0.01 | 0.03 | 0.10 | 2,104.88 |
| **Panel D: Sell side** | | | | | | | | |
| Secondary Market Sell | 31,697 | 99.97 | 802.28 | 0.00 | 3.00 | 7.65 | 25.69 | 58,462.74 |
| Secondary Market Sell/Existing Exposure | 31,697 | 0.09 | 0.16 | 0.00 | 0.01 | 0.02 | 0.07 | 1.00 |
| Holding Period Sellers | 31,638 | 105.09 | 86.06 | 1 | 36 | 86 | 155 | 701 |

*Note:* This table reports the descriptive statistics (number of observations, mean, standard deviation, minimum, $25^{th}$ percentile, median, $75^{th}$ percentile, and maximum) for the wallet-investor perspective (Panel A), token-property perspective (Panel B), as well as the buy side (Panel C) and sell side (Panel D). The sample includes 238,433 blockchain transactions from 2019 to 2021. Figure 2.2 in the Appendix illustrates the calculation scheme of the buy and the sell side. All variables are defined in Table A.1 in the Appendix.

Based on 238,433 blockchain transactions related to all real estate tokens in our sample, we identify 6,806 unique wallets representing the corresponding number of real estate token investors. The different number of observations per variable is due to different transactions and filtering methods, both of which serve to derive the respective variable of interest. From the wallet-investor perspective in Table 2.2 in Panel A, we document that one single investor invests in 10.2 properties on average. However, at least 25% of all investors have invested in only one property. One reason for this observation could be the novelty and peculiarity of real estate tokens. The respective investors do not yet hold a diversified real estate token portfolio. This result is in line with a previous study of ICO investors which finds that the main reason for a token investment is technological motives, followed by financial reasoning (Fisch et al., 2021). The maximum of 171 distinct properties out of 173 exemplifies that there are also investors who have invested in almost every property and have well-diversified tokenized real estate portfolios.[11] After converting the number of tokens into dollar holding amounts, we find that the mean of *Holdings per Investors as of Dec 2021* is 4,029.35 USD, and the median is 259.45 USD. The mean of *Holding Period all Investors as of Dec 2021* is 244.51 days with a maximum of 850 days, indicating that investors of the first STO are still holding the tokens.

If we switch to the token-property perspective in Panel B, we see a high dispersion and less concentration of ownership based on the mean of the normalized *HHI** of 0.03 both after the STO and as of December 2021. This result indicates that not only a few investors hold the majority of tokens, but that tokenization, in practice, provides broad access to real estate ownership for many small investors. This result aligns with the evidence of Swinkels (2023), who utilizes a smaller sample. The maxima of both *HHI** can be attributed to a not fully transferred project with a single investor who sold off large parts of the investment after the STO. Apart from the maxima, the overall distributions remain the same, suggesting that secondary market trading does not change the ownership structure. Digitized properties are held in the mean by 401.2 different investors. Even though we obverse extreme cases, such as one property in 1,173 wallets, this variable is affected by the amount of *Total Investment*, since most issued tokens amount to around 50 USD and a higher *Total Investment* enables more investors to invest in a particular property.

The analysis of blockchain transactions on the buy side in Panel C shows that investors spend 317.82 USD in the mean during the STO and a median amount of 57.96 USD, which approximately equals the value of one token. With a mean *Secondary Market Buy* amounting to 88.70 USD, investors appear to acquire tokens mainly during the STO, while secondary market purchases play a subordinate role. This finding is underpinned by the ratio *Secondary Market Buy/Existing Exposure*, which indicates that investors raise their

[11] Due to the pseudonymity of wallets on the blockchain and the fact that we can only trace back the issuing wallets of RealT, we cannot completely rule out the possibility that our maxima are influenced by other wallets used for handlings and shifts by the token issuer.

investment by a median value of 3% on the secondary market compared to their existing exposure.

Lastly, in Panel D, we examine the sell side. The *Secondary Market Sell* has a mean value of 99.97 USD. However, there exists a disparity in the number of observations between *Secondary Market Buy* and *Secondary Market Sell* due to the calculation of the daily balance, as explicated in Section 2.3.2. At the transaction-based level, each buy transaction corresponds to a sell transaction facilitated by the blockchain. Notably, in certain instances, a single sell transaction is associated with multiple buy transactions from different wallets (refer to transactions between wallet #2 and wallet #3 in Figure 2.2 in the Appendix). Consequently, we observe a lower number of *Secondary Market Sell* observations compared to the number of *Secondary Market Buy* observations, alongside a higher mean value for *Secondary Market Sell*. Additionally, the distribution of *Secondary Market Buy* and *Secondary Market Sell* exhibits similarity from the maximum to the 25th percentile.[12] The ratio *Secondary Market Sell/Existing Exposure* reveals that, in the mean, 9% of the existing exposure is sold, while the median value is 2%. The latter two variables highlight that most real estate token investors tend to hold their tokens and do not liquidate the investment quickly. The *Holding Period Sellers* shows that investors who sell their tokens hold them for 105.09 days in the mean before. This result is also consistent with Auer and Tercero-Lucas (2022), who find evidence of the increasingly popular *"hodling strategy"* among crypto investors who buy-and-hold tokens for a long time to avoid exposure to the short-term volatility in the crypto market.

### 2.4.2 Analysis of STO success determinants

To test our hypotheses for STO success, we run different regression specifications for the two success variables: funding time and speed. First, we sub-categorize funding time into *Funding Time until Success* for the successfully funded projects with OLS regressions (Models 1-2) and *Funding Time until Dec 2021* for all projects with parametric accelerated failure-time survival models with a lognormal distribution (Model 3), and loglogistic distribution (Model 4). We report the results in Table 2.3.

In the block of property characteristics for Hypothesis 1, only *Single Family* is positively related to the funding time of successfully funded and all projects. Based on the regression estimations, we find that *Single Family* increases the funding time of successfully funded projects by over 20 days in Models 1-2 and delays the success by around 79% ($e^{0.58} - 1$) for

[12] This observation suggests that the aggregation of sell transactions occurs within the range of transaction volumes below 3 USD (roughly the 25th percentile of both variables). To substantiate this claim, we conducted an unreported analysis utilizing kernel density plots for *Secondary Market Buy* and *Secondary Market Sell* observations across different transaction volume ranges. The plots reveal a large overlap between the two distributions. Consequently, the mean value of *Secondary Market Sell* is influenced by fewer observations.

Table 2.3: Determinants of Funding Time

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Funding Time until Success | | Funding Time until Dec 2021 | |
| | *OLS* | | *AFT* | |
| | | | *lognormal* | *loglogistic* |
| | (1) | (2) | (3) | (4) |
| Rent per Token p.a. | 10.05*** | 9.92*** | 0.20** | 0.19** |
| | (2.71) | (3.15) | (2.00) | (2.20) |
| Expected Yield | −1,392.25 | −519.07 | −57.31*** | −67.48*** |
| | (−1.53) | (−0.55) | (−3.18) | (−3.72) |
| Total Investment | −0.004 | −0.03 | 0.001 | 0.001* |
| | (−0.13) | (−0.91) | (1.47) | (1.78) |
| Age | 0.05 | −0.07 | 0.01 | 0.01* |
| | (0.17) | (−0.27) | (1.08) | (1.74) |
| Lot Size | 0.002 | 0.002 | −0.0000 | 0.0000 |
| | (1.16) | (1.13) | (−0.32) | (0.35) |
| Section 8 | −13.04 | −3.56 | 0.12 | −0.06 |
| | (−1.45) | (−0.38) | (0.39) | (−0.22) |
| Single Family | 24.84** | 21.68** | 0.47 | 0.58** |
| | (2.28) | (2.24) | (1.53) | (2.00) |
| Distance DTWN | 0.83 | 0.70 | 0.01 | 0.002 |
| | (0.39) | (0.34) | (0.12) | (0.05) |
| Detroit | 7.10 | 5.03 | 1.05*** | 1.27*** |
| | (0.46) | (0.36) | (3.21) | (3.83) |
| #Pictures | −0.89 | −0.09 | −0.03 | −0.01 |
| | (−0.56) | (−0.06) | (−0.96) | (−0.37) |
| Gas Fees | | 3.15** | 0.10*** | 0.09*** |
| | | (2.27) | (4.04) | (3.56) |
| Housing Market | | 0.54** | 0.01 | 0.01 |
| | | (1.96) | (0.88) | (0.78) |
| Constant | 126.00 | −44.36 | 6.53** | 7.02** |
| | (1.30) | (−0.36) | (2.26) | (2.50) |
| Quarter-Year FE | Yes | Yes | Yes | Yes |
| Observations | 122 | 122 | 164 | 164 |
| $R^2$ | 0.48 | 0.52 | / | / |
| Adjusted $R^2$ | 0.38 | 0.42 | / | / |
| Log Likelihood | / | / | −577.14 | −573.64 |
| $\chi^2$ (df = 21) | / | / | 178.48*** | 193.30*** |

*Note:* The table reports the results for the sub-sample of successfully funded STOs with the dependent variable *Funding Time until Success* in Models 1-2 estimating OLS regression with robust standard errors. Models 3-4 present the results of the Accelerated Failure-Time (AFT) models with a lognormal and loglogistic distribution for all STOs, including unsuccessful ones with the dependent variable *Funding Time until Dec 2021*. The table contains the coefficient estimates and the corresponding *t*-statistics; the coefficients for the AFT model need to be exponentiated to interpret them as time ratios. All of the models include quarter-year dummies for time fixed-effects. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table A.1 in the Appendix.

all projects in Model 4. The coefficients of *Detroit* and *Age* are significant for all projects in Model 4 and delay the success by 256% and 1%, respectively. Thus properties outside of *Detroit* – a city suffering from an enduring economic decline and shrinking population – are funded more quickly for reasons of diversification. In sum, we find supportive evidence in favor of Hypothesis 1 for funding time, i.e. that, the variables *Single Family*, *Detroit*, and *Age* are positively related to the success of an STO. However, since the remaining property-specific variables *Lot Size*, *Section 8*, and *Distance DTWN* are insignificant in all model specifications, we cannot provide further empirical support for Hypothesis 1. Particularly interesting is the irrelevance of the factors of size and location, which are typically important predictors in the real estate sector.

The campaign variable *#Pictures* is insignificant in all four models.[13] Therefore, we cannot provide empirical evidence for Hypothesis 2 and the common finding in CF that a more detailed description reduces information asymmetries and, hence, increases project success. The reason for this could be that, in contrast to conventional CF, in which information asymmetries are high (Courtney et al., 2017), the quality of a property can be determined more easily. Thus information asymmetries are, in general, lower for real estate tokens than for CF projects.

The coefficient of *Gas Fees* is significant and positively related to both sub-categories of funding time. For example, higher transaction costs delay the success by around 9% for all projects in Model 4. This finding aligns with Momtaz et al. (2022), who find that investors limit their token trading activity when transaction costs are high. In sum, we find supportive evidence for Hypothesis 3b that investors reduce their trading activity when blockchain-related demand-driven transaction costs increase, which makes real estate STOs less successful.

The *Housing Market* coefficient is only significant and positively connected to *Funding Time until Success* in Model 2. However, funding time positively correlates with *Total Investment* and, as both *Total Investment* and *Housing Market* increase in our sample over time, we observe a positive coefficient for *Housing Market*. Among the financial controls, *Expected Yield* is significant for all projects and decreases the funding time strongly since a higher *Expected Yield* makes a project more attractive for investors. In contrast, *Rent per Token p.a.* positively impacts the funding time in all models. This result emanates from the fact that *Rent per Token p.a.* is in the same range for most observations due to the setting of the token issuer; however, just a few STOs above the 75% percentile (see Table 2.1) have not been successful and are the reason for the counterintuitive direction of effect of the *Rent per Token p.a.* coefficient. The *Total Investment*, which is significant for all projects with a loglogistic distribution, delays the success by merely 0.1%.

[13] We do not anymore consider *#Characters* in the multivariate analysis, as outlined in Subsection 2.3.5; however, we find in unreported analysis that it is also insignificant.

Models 1-2 consider only successful projects, and the estimations could be subject to a survivorship bias. However, comparing the results of the models of the successfully funded projects (Models 1-2) with those of all projects (Models 3-4), we do not observe apparent differences in signs and significances of the coefficients that would indicate a bias. The results of the two AFT models with different distribution assumptions are similar.

To obtain the complete picture of STO success and to rule out effects caused by the magnitude of the *Total Investment* amount, we study the newly-constructed dependent variable speed and present the results in Table 2.4. Since the STO is more successful if it raises more money within a certain period, the signs' interpretation of the coefficients should be opposite to the previous analyses of the funding time. Again, we sub-categorize the dependent variable into *Speed until Success* in Models 1-2 and *Speed until Dec 2021* in Models 3-4 and run OLS regressions.

*Lot Size* and *Detroit* are significant variables within property characteristics in all models for the speed variables. *Lot Size* is positively associated with both speed variables. Properties in *Detroit* have a lower *Speed until Success* of 26,080 USD/day for successful projects and a lower *Speed until Dec 2021* of 13,260 USD/day for all projects. In line with the traditional real estate literature on location, this determinant is relevant, particularly for successfully funded projects. Since the majority of property characteristics are insignificant, we find only statistical support in favor of Hypothesis 1 for *Lot Size* and *Detroit*.

The campaign variable *#Pictures* is also insignificant for the speed variables.[14] The reason for this is probably the same as outlined above for the funding time. Consequently, we find no empirical evidence for Hypothesis 2.

We find a significant and negative relationship between the transaction costs *Gas Fees* and both speed variables, indicating that higher transaction costs are related to a lower level of STO success. For example, a one-standard-deviation increase in *Gas Fees* is associated with a 5,617 USD/day decrease in the *Speed until Dec 2021*. Compared to Model 2, the effect is more pronounced in terms of significance and magnitude of the coefficient for Model 4, which considers the whole sample. This finding is reasonable because this specification additionally considers unsuccessful projects whose success is more negatively affected by high transaction costs. Thus we find strong empirical support for Hypothesis 3b.

As assumed after taking the *Total Investment* into account for the dependent variable, *Housing Market* is insignificant. Among the financial characteristics, *Rent per Token p.a.* again has a negative impact in Models 2 and 4. The coefficient of *Expected Yield* is significant and positive on the 10% level in Models 1 and 4 and highly increases the speed of funding.

The adjusted $R^2$ ranges from 0.36 to 0.53. In summary, we observe that concerning both

[14]The same applies if we include *#Characters*.

Table 2.4: Determinants of Speed

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Speed until Success | | Speed until Dec 2021 | |
| | (1) | (2) | (3) | (4) |
| Rent per Token p.a. | −3.60 | −3.94* | −2.84 | −3.92* |
| | (−1.60) | (−1.74) | (−1.32) | (−1.75) |
| Expected Yield | 656.78* | 737.05 | 481.33 | 666.49* |
| | (1.71) | (1.43) | (1.53) | (1.73) |
| Age | −0.04 | −0.03 | 0.004 | 0.07 |
| | (−0.36) | (−0.25) | (0.04) | (0.61) |
| Lot size | 0.003** | 0.003** | 0.002* | 0.003** |
| | (2.00) | (2.12) | (1.83) | (2.19) |
| Section 8 | −2.79 | −3.58 | 0.19 | −1.91 |
| | (−0.54) | (−0.72) | (0.04) | (−0.44) |
| Single Family | −2.96 | −2.34 | −0.84 | −1.41 |
| | (−0.64) | (−0.53) | (−0.24) | (−0.42) |
| Distance DTWN | −1.28 | −1.19 | −0.24 | −0.18 |
| | (−1.51) | (−1.47) | (−0.31) | (−0.22) |
| Detroit | −28.70*** | −26.08*** | −16.79*** | −13.26** |
| | (−3.30) | (−3.02) | (−2.77) | (−2.36) |
| #Pictures | 0.63 | 0.57 | 0.88 | 0.45 |
| | (0.78) | (0.71) | (1.34) | (0.73) |
| Gas Fees | | −0.92** | | −1.24*** |
| | | (−2.13) | | (−3.14) |
| Housing Market | | 0.12 | | 0.18 |
| | | (0.76) | | (1.29) |
| Constant | −19.75 | −43.90 | −31.76 | −66.76 |
| | (−0.42) | (−0.54) | (−0.71) | (−1.08) |
| Quarter-Year FE | Yes | Yes | Yes | Yes |
| Observations | 122 | 122 | 164 | 164 |
| $R^2$ | 0.59 | 0.61 | 0.43 | 0.48 |
| Adjusted $R^2$ | 0.51 | 0.53 | 0.36 | 0.41 |

*Note:* The table reports the results for the sub-sample of successfully funded STOs with the dependent variable *Speed until Success* in Models 1-2 and for the whole sample with *Speed until Dec 2021* in Models 3-4 estimating OLS regression with robust standard errors. The table reports the coefficient estimates and the corresponding *t*-statistics; all of the models include quarter-year dummies for time fixed-effects. The dependent variable *Speed until Success* is the fraction of *Total Investment/Funding Time until Success* and *Speed until Dec 2021* is the fraction of *Total Investment/Funding Time until Dec 2021*. The symbols $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table A.1 in the Appendix.

speed sub-categories, the traditional property characteristics of size and location (*Lot Size* and *Detroit*) are relevant determinants of STO success in addition to transaction costs on the crypto market (*Gas Fees*) and financial controls. The coefficient of *Lot Size* has the same magnitude for all models, *Detroit* shows a larger effect when restricting to only successfully funded projects. The unattractive location of the city of *Detroit* reduces the speed for successfully funded projects. *Gas Fees* is the only variable with a stronger effect when considering the entire sample, including unsuccessfully funded projects whose success is more negatively affected by high transaction costs. In line with Table 2.3, we do not observe apparent differences in the signs and significances between the models relying only on successfully funded projects and those comprising all projects.

### 2.4.3 Analysis of funding determinants

Table 2.5: Funding Determinants

| | *Dependent variable:* | |
|---|---|---|
| | Inflow | Outflow |
| | (1) | (2) |
| ETH Price | $139.72^{***}$ | 2.65 |
| | (3.39) | (0.52) |
| Gas Fees | $-1.28^{***}$ | $-0.10^{***}$ |
| | (−11.04) | (−6.78) |
| ETH Shock | $-607.06^{***}$ | −33.96 |
| | (−2.81) | (−1.29) |
| Gas Shock | $-489.47^{**}$ | $49.25^{*}$ |
| | (-2.20) | (1.81) |
| One-month Treasury | $1,202.02^{*}$ | 64.15 |
| | (1.86) | (0.73) |
| Ten-year Treasury | 315.63 | −28.49 |
| | (0.51) | (−0.37) |
| ADS Index | −32.89 | $-8.99^{**}$ |
| | (−0.90) | (−2.01) |
| Individual FE | Yes | Yes |
| Time FE | Yes | Yes |
| Observations | 18,182 | 17,606 |
| $R^2$ | 0.062 | 0.049 |
| Adjusted $R^2$ | 0.053 | 0.040 |

*Note:* This table presents the analysis of funding determinants based on OLS regressions. It reports the coefficient estimates and the corresponding $t$-statistics. The dependent variable is either daily *Inflow* or daily *Outflow* per property in a fixed-effects panel regression with individual and time-fixed effects. The symbols $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table A.1 in the Appendix.

In the following, we study the funding determinants to analyze the entire crypto market on the macro-level and to account for its particularities over time. In Model 1 of Table 2.5, we present the regression estimations for the dependent variable daily *Inflows* per property from investors purchasing tokens. Model 2 exemplifies the daily *Outflows* per property from investors selling tokens.

At first, we analyze the determinants that relate specifically to the crypto market. Model 1 exhibits a significant and negative coefficient of the *ETH Price* for *Inflows*, and no significance for *Outflows*. An increase of 1 USD in the *ETH Price* is associated with an increase of 139.72 USD in daily *Inflows* per property. Consequently, the crypto market sentiment appears to be a relevant predictor for capital *Inflows* on the market for real estate tokens, probably because crypto investors are subject to herding behavior caused by the sentiment on the crypto market. The results of *ETH Price* for *Inflows* provide statistical support for Hypothesis 3a, whereas we find no evidence of *Outflows* for Hypothesis 3a. Further, the coefficients of *Gas Fees* are negatively related to both capital *Inflows* and *Outflows*. The results of *Gas Fees* are consistent with Hypothesis 3b, that investors limit their trading activity to avoid high transaction costs, regardless of whether *Inflows* or *Outflows* are considered. It is worth noting that the crypto market sentiment *ETH Price* is not significantly related to *Outflows*, but crypto market transaction costs are. The reason for this could be that investors who have already decided to liquidate the tokens are timing the sale depending on transaction costs, as these directly affect their return on investment. Both dummy variables for short-term shocks on the crypto market are significant and negatively associated with *Inflows*, although with low or no significance for *Outflows*. To be more precise, the coefficient of *ETH Shock* decreases *Inflows* for 607.06 USD when the cumulative Ether return decreased for five days prior to the *Inflow*. The effect for a *Gas Shock* is less pronounced and implies that the occurrence of a *Gas Shock* decreases *Inflows* by 489.47 USD. The shock results for *Inflows* align with our crypto-market related Hypotheses 3a and 3b since a shock of the crypto market sentiment and the transaction costs reduce *Inflows*. Interestingly, short-term shocks in the crypto market do not seem to play a major role in *Outflows*. Possibly this is because regular cash flows from the tokens are based on rent payments and are not affected by short-term crypto shocks, so there is no incentive to sell and cause an *Outflow*. Consequently, we cannot provide empirical evidence for *Outflows* and the shock variables for our Hypotheses 3a and 3b.

Regarding the macroeconomic factors *One-month Treasury*, *Ten-year Treasury*, and the *ADS Index*, we find occasional and low significances for both *Inflows* and *Outflows*. The short-term interest rate has a positive and significant influence on *Inflows*, whereas long-term interest is insignificant for both capital flows. An increase in the *ADS Index*, indicating progressively better-than-average conditions for doing business, significantly reduces *Outflows*. Thus the macroeconomic situation does not appear to be an essential criterion in the decision-making process of a real estate token investor. Our finding is consistent with Yermack (2015) and Bianchi (2020), who conclude that macroeconomic events and factors do not drive trading volumes and daily exchange rates of the main cryptocurrencies.

In sum, we find that the crypto market-related transaction costs, sentiment, and the corresponding short-term shocks are relevant predictors of daily *Inflows* for purchasing tokens rather than daily *Outflows* of selling tokens.

## 2.5 Robustness and further analysis

### 2.5.1 Adjustment of financing threshold

It is common practice that RealT retains around 5% tokens of a property to ensure liquidity on secondary markets in the future, which is why we define the success of a project as transferring 95% of the tokens. We vary the threshold for the definition of "successfully" funded between 90% and 100% in unreported analyses. Our results remain qualitatively unchanged and robust for these adjustments.

### 2.5.2 Analysis of the determinants of Total Investment and Expected Yield

Digging deeper into the structure of the projects offered in the STO, we investigate the determinants of the money-oriented variable *Total Investment* and present the estimations in Models 1-2 in Table A.3 in the Appendix. Regarding the financial variables, the coefficient of *Expected Yield* is significant and negative in both model specifications. When considering the property characteristics, we find that lower quality properties, which are older and have higher risk diversification among tenants, are offered with a lower *Total Investment.* The variables *Lot Size* and *Section 8* have a significant positive impact across all models. The lower risk of a rent default of *Section 8* supported rents is associated with a higher *Total Investment.* The coefficient of the CF variable *#Pictures* is insignificant, probably because this variable is less relevant to the token issuer. Both market-related variables *Gas Fees* and *Housing Market* are insignificant. In the next step, we switch from the dollar amount of *Total Investment* to a return perspective and study the determinants of *Expected Yield* in Models 3-4 in Table A.3. As expected, the *Rent per Token p.a.* is positively related to the *Expected Yield.* In line with the previous results for *Total Investment*, the coefficient for *Single Family* is also negatively related to *Expected Yield.* The coefficient of *Distance DTWN* indicates that a higher distance from downtown reduces the yield due to lower rent in more unattractive locations further afield. The *Housing Market* is negatively associated with the *Expected Yield.* A higher housing index is connected with higher housing and token values and, consequently, a lower *Expected Yield.*

In summation, only for *Single Family* do we find consistent signs and significances for both *Total Investment* and *Expected Yield*, while the evidence for the remaining variables is mixed. While crypto-market transaction costs are significantly related to the success of the STO as measured by funding time and speed, see Subsection 2.3.3, they are not related to the *ex-ante* set structure of the offered projects by the token issuer.

## 2.6 Conclusion

Digitization is transforming various industries, including the financial and real estate sectors. We highlight the new way of securitizing assets, using the blockchain and digital security tokens and their issuance processes through STOs. Real estate has been identified as a suitable market for tokenization due to this technical innovation overcoming the drawbacks of direct real estate investments, such as high entry barriers and illiquidity. Technical features facilitate the investment of small amounts of money, eliminate the need for financial intermediaries, and increase transaction speed, consequently lowering the costs for all parties involved. Thus investors can diversify their portfolios more easily among asset classes and countries. The tokens can be traded after issuance on secondary markets, which enables liquidity. Even though the possibility of fractional ownership already exists in indirect investment instruments, such as funds or REITs, real estate tokens come closer to direct ownership with controlling rights.

Based on STO data of 173 real estate tokens and more than 238,433 blockchain transactions, we analyze investor behavior, the determinants of STO success, and capital flows over time. During our observation period, real estate token investors hold a mean of 10 different tokens and an investment amount of 4,030 USD, which shows that investors do not yet hold well-diversified real estate token portfolios. Ownership of the properties is not concentrated on some large investors emphasizing that tokenization provides broad access to real estate ownership for many small investors. Further, we conclude that investors acquire tokens mainly during the STO, while the secondary market plays a subordinate role in token purchases and sales. This study's primary success variable of interest is the mean funded investment amount per day (*Speed*). Property-specific fundamentals and crypto market-related transaction costs are positively related to STO success, along with financial characteristics. In line with the well-known explanatory power of location factors in real estate, we find that location is another important determinant of STO success. The success of STOs appears to be independent of crowdfunding characteristics, probably because a property's quality can be determined more easily, and information asymmetries are lower than for conventional crowdfunding projects. Investors seek diversification possibilities through location choice to reduce the idiosyncratic cash flow risk of the investment and try to evade high transaction costs that reduce their return. From the perspective of capital inflows (token purchases) and capital outflows (token sales) per day, we find that real estate token investors pay equal attention to the crypto market-specific sentiment and transaction costs when purchasing tokens. In contrast, only the transaction costs directly reducing the return on investment are relevant for sales. Both short-term shocks have a strong negative impact on capital inflows. Macroeconomic factors appear to have little effect on capital flows in general. These results highlight the importance of considering the specific crypto market environment and the characteristics of the underlying asset class for real asset tokenization.

A limitation is our small sample size of 173 projects, resulting from the fact that tokens are becoming the focus of public attention. Our results may not be generalized, as they are derived from observing a small but growing number of crypto enthusiasts familiar with the technical background. Therefore, there is an avenue for future research to test and verify our results in a broader sample regarding other asset classes, periods examined, geographic scope related to different jurisdictions and implementation options, and the number of investors.

Our study has practical and policy implications. As discussed at the G-7 meeting in May 2022, various regulators and politicians have called for accelerating global crypto regulations for better financial stability to enable innovative digital finance solutions and investor protection. Our findings contribute to the last two objectives of this regulatory effort. We find that the particularities of the crypto market are essential determinants for the success of real estate STOs and capital flows. This result may raise the concern that token investors mainly follow trends that do not reflect the fundamental asset characteristics, implying a high need for consumer protection. Such technical innovation can also support investors in building more diversified portfolios. However, according to our results, this possibility has not been used sufficiently until now. Regulators must find a compromise to achieve investor protection and foster the development of digital finance products without suppressing the opportunities for technology and innovation.

# Appendix

Table A.1: Definition of all Variables

| | | |
|---|---|---|
| **Blockchain transaction analysis** | | |
| *Properties per Investor* | Number of distinct real estate tokens per unique wallet | Own calculations |
| *Holdings per Investor as of Dec 2021* | Dollar Holdings per Investor as of 31 Dec 2021 | Own calculations |
| *Holding Period all Investors as of Dec 2021* | Holding Period of all Investors in Days as of 31 Dec 2021 | Own calculations |
| *HHI* | Herfindahl-Hirschman Index per property | Own calculations |
| *HHI* STO* | Normalized Herfindahl-Hirschman Index per property after the tokens have been transferred during the STO, based on the actual quantity of issued tokens comprising successful and unsuccessful STOs (between 0 and 1) | Own calculations |
| *HHI* as of Dec 2021* | Normalized Herfindahl-Hirschman Index per property as of 31 Dec 2021 (between 0 and 1) | Own calculations |
| *Investors per Property* | Number of unique wallets per real estate token | Own calculations |
| *STO Buy* | Amount of money of buy transactions during the STO | Own calculations |
| *Secondary Market Buy* | Amount of money of secondary market buy transactions in USD | Own calculations |
| *Secondary Market Buy/ Existing Exposure* | Percentage ratio of the *Secondary Market Buy* to the existing exposure | Own calculations |
| *Secondary Market Sell* | Amount of money of secondary market sell transactions in USD | Own calculations |
| *Secondary Market Sell/ Existing Exposure* | Percentage ratio of the *Secondary Market Buy* to the existing exposure | Own calculations |
| *Holding Period Sellers* | Holding Period of investors selling tokens in days | Own calculations |
| **Analysis of STO determinants** | | |
| Dependent variables | | |
| *Funding Time until Success* | Number of days until all tokens (95 percent, since RealT keeps around 5 percent to themselves) are transferred to wallets. For this variable, only successful projects are considered. The start date of the funding period is derived from the HTML code on the website and the end date from the blockchain explorers. | Own calculations |
| *Funding Time until Dec 2021* | Number of days until all tokens (95 percent, since RealT keeps around 5 percent to themselves) are transferred to wallets. For this variable, both successful and unsuccessful projects are considered. The start date of the funding period is derived from the HTML code on the website and the end date from the blockchain explorers. | Own calculations |
| *Speed until Success* | 95% of *Total Investment* divided through *Funding Time until Success*, (in thousands USD/day) for the sub-sample of successful projects | Own calculations |
| *Speed until Dec 2021* | 95% of *Total Investment* divided through *Funding Time until Dec 2021* (in thousands USD/day) for all projects. For projects that have not been successfully funded until the end of our observation period and are on the market longer than the mean time of *Funding Time until Success*, the *Speed until Dec 2021* is equated to 0. For projects that have not been successfully funded until the end of the observation period and are on the market shorter than the mean time of | Own calculations |

| | | |
|---|---|---|
| | *Funding Time until Success*, the actual amount of money raised is used instead of *Total Investment.* | |
| Explanatory variables | | |
| *Rent per Token p.a.* | Rent per token per year | RealT |
| *Total Investment* | Amount of money required for the funding, technically the number of tokens multiplied by the token price (in thousands USD) | RealT |
| *Expected yield* | Expected income calculated as net rent divided by token price | RealT |
| *Age* | Difference between the publication date of the project and the construction year | RealT |
| *Lot Size* | Size of the real estate (in square foot) | RealT |
| *Section 8* | Percentage of rents supported by Section 8 in the whole property | RealT |
| *Single Family* | A dummy variable for the property type of use that shows whether the building is a single-tenant property, 0 otherwise. | RealT |
| *Distance DTWN* | Distance to downtown in miles | Walk Score |
| *Detroit* | A dummy variable that shows whether the property is located in Detroit, 0 otherwise. | RealT |
| *#Pictures* | Absolute numbers of pictures of the property published on the platform | RealT |
| *#Characters* | Absolute number of characters of the descriptive text of the project on the platform | RealT |
| *Gas Fees* | Transaction costs on the Ethereum blockchain on the day the project is published online or on the day of the observation, converted to USD | Coinmarketcap |
| *Housing Market* | S&P Case-Shiller Home Price Index for the corresponding region, lagged for one month | S&P Dow Jones Indices |
| **Analysis of funding determinants** | | |
| Dependent variables | | |
| *Inflow* | Daily capital inflows per property per day in USD (STO and secondary market buy transactions) | Own calculations |
| *Outflow* | Daily capital outflows per property per day in USD (secondary market sell transactions) | Own calculations |
| Explanatory variables | | |
| *One-month Treasury* | Market yield on US Treasury Securities at 1-month constant maturity, quoted on an investment basis | FRED, Federal Reserve Bank of St. Louis |
| *Ten-year Treasury* | Market yield on US Treasury Securities at 10-year constant maturity, quoted on an investment basis | FRED, Federal Reserve Bank of St. Louis |
| *ADS Index* | Aruoba-Diebold-Scotti (ADS) Business Condition Index based on Aruoba et al. (2009) to measure macro-economic activity at a daily frequency | Federal Reserve Bank of Philadelphia |
| *ETH Price* | Cumulative return of Ether over a period of five days before the observation | Coinmarketcap |
| *ETH Shock* | A dummy variable that equals one if the cumulative return of *ETHPrice* decreased by more than 5% over a five-day window before the observation, 0 otherwise. | Own calculations |
| *Gas Shock* | A dummy variable that equals one if the *Gas Fees* cumulatively increased by more than 5% over a five-day window before the observation, 0 otherwise. | Own calculations |

*Note:* List and definitions of all variables and the corresponding sources. RealT as a source corresponds to information obtained from RealToken's website.

Table A.2: Correlation Table

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Total Investment | 1 | | | | | | | | | | | | | |
| (2) Expected Yield | −0.03 | 1 | | | | | | | | | | | | |
| (3) Funding Time until Success | 0.01 | 0.06 | 1 | 1 | | | | | | | | | | |
| (4) Funding Time until Dec 2021 | 0.01 | 0.06 | 1 | 1 | | | | | | | | | | |
| (5) Speed until Success | 0.43 | 0.01 | −0.37 | −0.37 | 1 | 1 | | | | | | | | |
| (6) Speed until Dec 2021 | 0.43 | 0.01 | −0.37 | −0.37 | 1 | 1 | | | | | | | | |
| (7) Rent per Token p.a | 0.26 | 0.42 | 0.29 | 0.29 | −0.04 | −0.04 | 1 | | | | | | | |
| (8) Age | 0.12 | 0.03 | −0.17 | −0.17 | 0.24 | 0.24 | −0.24 | 1 | | | | | | |
| (9) Lot Size | 0.55 | 0.24 | 0.13 | 0.13 | 0.36 | 0.36 | 0.60 | −0.17 | 1 | | | | | |
| (10) Section 8 | 0.19 | −0.19 | −0.23 | −0.23 | 0.08 | 0.08 | 0.06 | −0.02 | 0.05 | 1 | | | | |
| (11) Distance DTWN | −0.08 | −0.02 | 0.03 | 0.03 | −0.13 | −0.13 | 0.13 | −0.02 | 0.08 | 0.03 | 1 | | | |
| (12) #Pictures | 0.30 | 0.05 | −0.18 | −0.18 | 0.38 | 0.38 | 0.14 | 0.11 | 0.32 | −0.02 | −0.01 | 1 | | |
| (13) Gas Fees | 0.19 | −0.03 | 0.39 | 0.39 | −0.12 | −0.12 | −0.16 | 0.12 | −0.01 | −0.28 | 0.04 | −0.11 | 1 | |
| (14) Housing Market | 0.34 | −0.49 | 0.06 | 0.06 | 0.24 | 0.24 | −0.28 | 0.29 | −0.08 | −0.09 | −0.12 | 0.01 | 0.27 | 1 |

*Note:* This table reports the Bravais-Pearson correlation coefficients of the dependent and explanatory variables. All variables are defined in Table A.1 in the Appendix.

Table A.3: Determinants of Total Investment and Expected Yield

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Total Investment | | Expected Yield | |
| | (1) | (2) | (3) | (4) |
| Rent per token p.a. | −1.61 | −8.84 | 0.002** | 0.002*** |
| | (−0.11) | (−0.56) | (2.47) | (3.91) |
| Expected Yield | −6,629.80** | −4,471.23* | | |
| | (−2.55) | (−1.77) | | |
| Age | −2.74** | −2.31* | 0.0001** | 0.0000 |
| | (−2.40) | (−1.82) | (2.33) | (0.60) |
| Lot Size | 0.02*** | 0.02*** | 0.0000 | −0.0000 |
| | (2.84) | (3.02) | (1.57) | (−0.07) |
| Section 8 | 139.29** | 149.49*** | −0.002 | −0.003 |
| | (2.56) | (2.75) | (−1.27) | (−1.64) |
| Single Family | −240.42*** | −238.69*** | −0.004*** | −0.003** |
| | (−5.74) | (−5.75) | (−2.73) | (−2.25) |
| Distance DTWN | −8.08 | −6.60 | −0.001** | −0.001*** |
| | (−1.25) | (−1.04) | (−2.18) | (-2.82) |
| Detroit | −10.88 | 6.95 | 0.01*** | 0.004** |
| | (−0.22) | (0.13) | (3.30) | (1.99) |
| #Pictures | 5.99* | 3.67 | −0.0002 | 0.0002 |
| | (1.67) | (0.89) | (−1.01) | (0.65) |
| Gas Fees | | 3.11 | | −0.0001 |
| | | (1.19) | | (−1.09) |
| Housing Market | | 1.42 | | −0.0002*** |
| | | | (1.53) | (−4.17) |
| Constant | 1,289.40*** | 887.10** | 0.09*** | 0.11*** |
| | (3.95) | (2.32) | (5.54) | (9.90) |
| Quarter-Year FE | Yes | Yes | Yes | Yes |
| Observations | 165 | 165 | 165 | 165 |
| $R^2$ | 0.58 | 0.70 | 0.65 | 0.66 |
| Adjusted $R^2$ | 0.54 | 0.66 | 0.61 | 0.61 |

*Note:* This table presents the results of OLS regression for the dependent variables *Total Investments* and *Expected Yield* with robust standard errors. The table reports the coefficient estimates and the corresponding $t$-statistics; all models include quarter-year dummies for annually and quarterly fixed-effects. The dependent variable *Total Investment* is measured in thousands USD. The symbols $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table A.1 in the Appendix.

## Conflicts of Interest

One author bought a few digital tokens issued by the company RealT so that they could describe the process of tokenization. The current value is lower than 200 USD. The other authors have no commercial relationship with the company or management whose data we mostly rely on.

## Acknowledgements

We appreciate the helpful comments and suggestions from Laurens Swinkels, Andreia Dionisio, and other participants at the 2022 CryptoAssets and Digital Asset Investment Conference of the Future Finance and Economics Association (Rennes), 2022 ERES Meeting (Milan), Cryptocurrency Research Conference 2022 (Durham), NTNU Conference 2022 (Trondheim), EFA Workshop on FinTech – Blockchain & Cryptocurrency (Barcelona), 5th Annual REALPAC/Toronto Metropolitan University Research Symposium, and 2023 ARES Annual Meeting and Conference (San Antonio, Texas).

# Chapter 3

# German FinTech companies: A market overview and volume estimates

This research project is joint work with Gregor Dorfleitner (University of Regensburg) and Julia Kreppmeier (University of Regensburg). The paper has been published as: Dorfleitner, G., Kreppmeier, J., Laschinger, R. (2023). German FinTech companies: A market overview and volume estimates. *Credit and Capital Markets*, Volume 56, Issue 1, pp. 103–118.

**Abstract** The FinTech market in Germany is a dynamic and growing field that is difficult to observe in its entirety. This report provides a hand-collected market overview of the FinTech market in Germany, as well as an application case in terms of volume estimates for the financing and asset management segments through December 2021. The data includes various verified characteristics of 978 unique companies that can be classified under the financial technology sector and operate in Germany. Each observation represents a company with 24 variables, including name, address, legal form, founders with corresponding LinkedIn accounts, registration number or company ID, assignment to FinTech segments and sub-segments, banking cooperation, URL address, local court, former name, operating status. We provide the description of the variables as well as a taxonomy to categorize FinTechs. The dataset contains both established companies and startups and presents valuable information for researchers, practitioners and also regulators.

**Keywords** FinTech, Germany, Start-Up, Financial Technology, Digital Finance, Entrepreneurship, Supervision

**JEL** G10, G20, G28, K20, L81, M13

## 3.1 Introduction

The importance and market volumes of FinTech companies (FinTechs) have been growing for a number of years, making FinTechs a very relevant subject in the academic context as well as for practitioners and regulators. Due to the predominantly digital nature of FinTechs, these companies are often only observable through their web presence. Likewise, they are not monitored by any regulator, at least not in the early stage, which is the reason why there have been few centralized captures or aggregated industry reports. This report is divided into two parts. First, we describe the companies and variables included in our aggregated German FinTech database as of December 2021. Using the German FinTech list by Dorfleitner et al. (2017) as a starting point, we have collected aggregate information on 978 FinTech-related companies that are or were active in Germany. Second, as an application case of the provided data, we present market volume estimates for the FinTech segments of financing and asset management until December 2021.

## 3.2 Data description

The data set is accessible on the Mendeley Data repository (Dorfleitner et al., 2023b). The data can be downloaded from the URL: https://doi.org/10.17632/438ytjyzxk.2 in an open access format.

### 3.2.1 Data collection

Our data were acquired in the following manner. The starting point was the FinTech list of Dorfleitner et al. (2017). This list already consists of hand-collected data over the years 2015 and 2016. In a similar vein, we continuously collected data until December 2021 using specific and topic-related databases (Crunchbase, BvD Dafne, German Company Register, Trade Register Excerpts), FinTech and bank websites as well as with structural Google searches. The entries and properties, specifically the operating status, were checked in regular time-intervals throughout the collection process over the years. The aim of the collection procedure was to find and identify all relevant FinTechs operating in Germany with a structured approach. Different databases and websites were used to obtain an overview of the market. The dataset was repeatedly updated and verified throughout the years within this process. An association to the segment of operations was conducted. Through structured Google searches the operating status was checked.

### 3.2.2 Variables description

Table 3.1 shows the overview of all variables in the dataset and describes the type and content of each variable. Note that for some of the 978 FinTech companies, some variables have missing values, which are marked NA.

The classification of FinTechs into segments and subsegments is generally based on the taxonomy of Dorfleitner et al., 2017, pp. 6-10, which is displayed in Figure 3.1. In order to take account of more recent developments in the market, we are also including the subsegment “BigTechs” for the payment services of BigTechs companies such as Amazon Pay, ApplePay and Google Pay under the segment “Payments”. In addition, we assign FinTechs operating in the field of blockchain and distributed ledger technology to the "Blockchain and cryptocurrencies" subsegment, which is subordinate to the "Payments" segment, although not all of them have business activities related to payment services. Companies offering services in the field of "RegTech" (Regulatory Technology) are only considered if there is a clear intersection with financial services and thus FinTech. They are assigned to a (sub-) segment according to the specific service provided, this is in the case of our dataset mostly “Technology, IT and Infrastructure” with services e.g., to detect financial fraud or ID-based for KYC purposes.

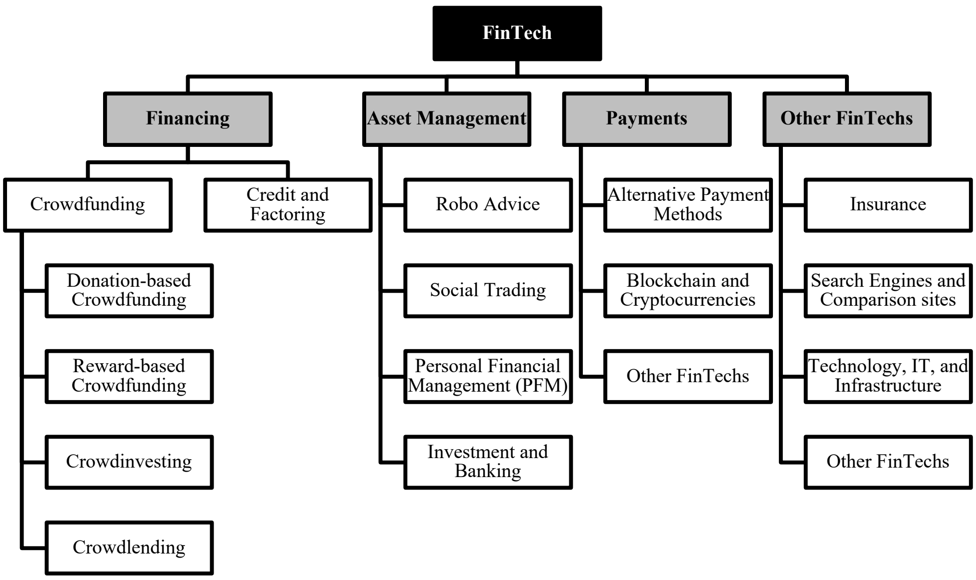



Figure 3.1: Taxonomy of FinTech companies according to Dorfleitner et al., 2017, p. 7.

This dataset was created to identify all relevant FinTechs operating in Germany. Therefore, a structured approach was used combining different databases and websites, as listed above, to obtain and verify a possibly complete overview of the market. The dataset was repeatedly updated and verified throughout the years within this process. Furthermore, each FinTech was assigned to one (sub-)segment in which its main operations take place.

Table 3.1: Variables description

| Variable | Type | Description |
|---|---|---|
| ID | Numeric | Unique identifier for each FinTech |
| Name | Character | Name of each FinTech |
| Status | Binary | FinTech is active up until 31.12.2021 |
| Original German | Binary | 1: FinTech is founded originally in Germany; 0: just operating in Germany |
| Founding year | Numeric | Year the FinTech was founded |
| Founder | Character | Name of the founder or founding company, either name of a natural person or company name, if several founders separated by ; |
| Founder (LinkedIn) | HTML | Link to the LinkedIn Profile, separated by ; |
| Legal Name | Character | Name of the FinTech according to company register/law |
| Legal Form | Character | Legal form of the FinTech according to law from company register |
| Street | Character | Street name of the FinTech according to the company register |
| Postal Code | Numeric | Postal code of the FinTech according to the company register |
| City | Character | City of the FinTech according to the company register |
| Country | Character | City of the FinTech according to the company register |
| Register Number / Company ID / LEI | Character | Register number / company ID / LEI of the FinTech |
| Segment / | Categorical | Association to an operating segment according to Fig. 1 below and description below (according to Dorfleitner et al., 2017) |
| Subsegment / | Categorical | Association to an operating subsegment according to Fig. 1 below and description below (according to Dorfleitner et al., 2017) |
| Bank Cooperation | Binary | 1: There exists a cooperation with a private/commercial bank; 0 otherwise |
| Homepage | HTML | Homepage of the FinTech |
| E-Mail | Character | E-Mail address of the FinTech |
| Insolvency | Binary | 1: FinTech is undergoing insolvency proceedings; 0 otherwise |
| Liquidation | Binary | 1: FinTech has been liquidated; 0 otherwise |
| Date of Inactivity | Date | Date of cessation or date of opening insolvency proceedings or date of liquidation |
| Local court | Character | Local court in Germany of the FinTech, if the company is resident in Germany |
| Former name | Character | Former name(s) of the FinTech, if the company was renamed |

Through structured Google searches the operating status was checked on a regular basis.

### 3.2.3 Descriptive statistics

Figures 3.2 and 3.3 show the number of companies identified in the various segments according to the taxonomy of Dorfleitner et al. (2017). It should be noted that there is no uniform distribution across the various segments. For example, at the end of 2021, most FinTechs are to be found in the payments segment with a number of 191, followed by the broad technology, IT and infrastructure segment with 127 companies. A progressive maturation of companies can be observed across all segments. At the same time, it should be emphasized at this point that the number of companies does not reflect the business volumes of the individual segments.

Figure 3 differentiates within the various segments based on the activity status of the FinTechs. The dataset also includes these inactive companies to ensure a survivorship bias-free dataset for further studies. The dataset contains an unknown number of companies that can still be reached via a website, but probably no longer have any business activity. Overall, it is noticeable that especially in the subsegments crowdinvesting and donation- and reward-based crowdfunding the highest shares of inactive companies were found. We also note that, in contrast to the venture capital industry, a large proportion of FinTechs are still active. Therefore, we additionally display in Figure 3.4 the average age per subsegment and differentiate between active and inactive FinTechs, whereby we can only calculate the age for 110 out of 172 inactive companies because of data availability. We cannot observe in any subsegment that the average age of active companies is close to that of inactive companies, which would explain the low number of inactive companies compared to the venture capital sector.

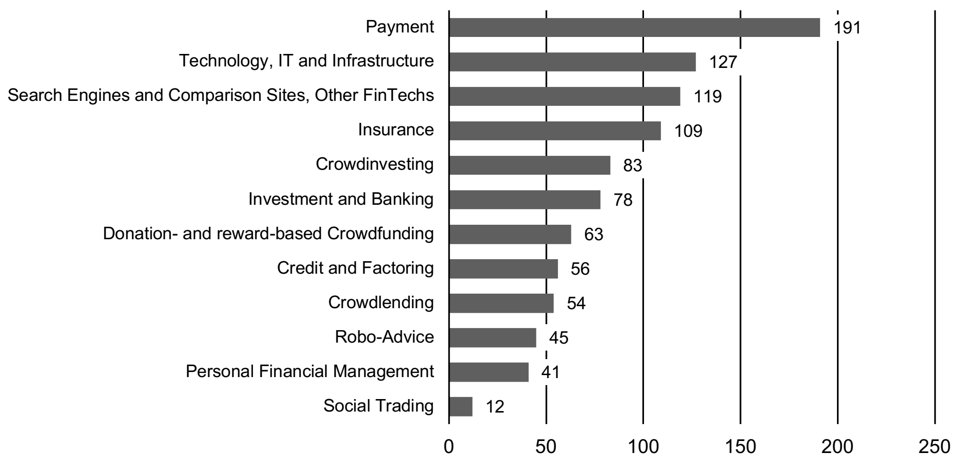



Figure 3.2: Absolute frequency of subsegments in our dataset.

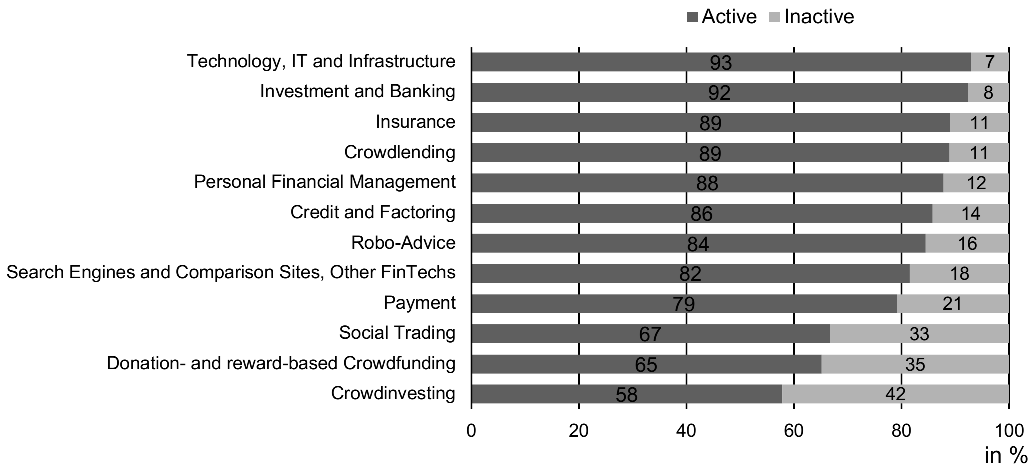



Figure 3.3: Relative frequency of active and inactive FinTechs in each subsegment.

### 3.2.4 Previous use of the data in research

The first version of the dataset and the categorization is based on Dorfleitner et al. (2017). Afterwards, estimations for the German market volume were performed for several years and segments, see for instance Dorfleitner et al. (2020) and Dorfleitner and Hornuf (2023). Based on the observed German FinTech companies, empirical studies related to data protection and the General Data Protection Regulation matched with the privacy policies were performed with simple descriptives by Dorfleitner and Hornuf (2019) or with the help of textual data mining and in multivariate analysis by Dorfleitner et al. (2023a).

## 3.3 Application case of the dataset: Estimation of market volumes of German FinTech segments

In this section, we present the estimation of the market volumes of German FinTechs as an application case for the dataset presented above. Based on the taxonomy of Dorfleitner et al. (2017), we focus on the financing and asset management segment. We exclude the payment segment as we do not have access to the transaction volumes of large players such as Paypal or ApplePay, which account for the majority of the market share in this segment. In addition, we exclude the Other FinTechs segment as for these companies data on market volumes cannot be collected in a comparable way.

To this end, we estimate the market volumes of 434 FinTechs, of which 341 are still active. To estimate the market volumes for the year 2021 in the each subsegment, we consider those three to five companies that had the highest market shares in 2020 and estimate their market volume in 2021 with the estimation and research techniques displayed in Dorfleitner

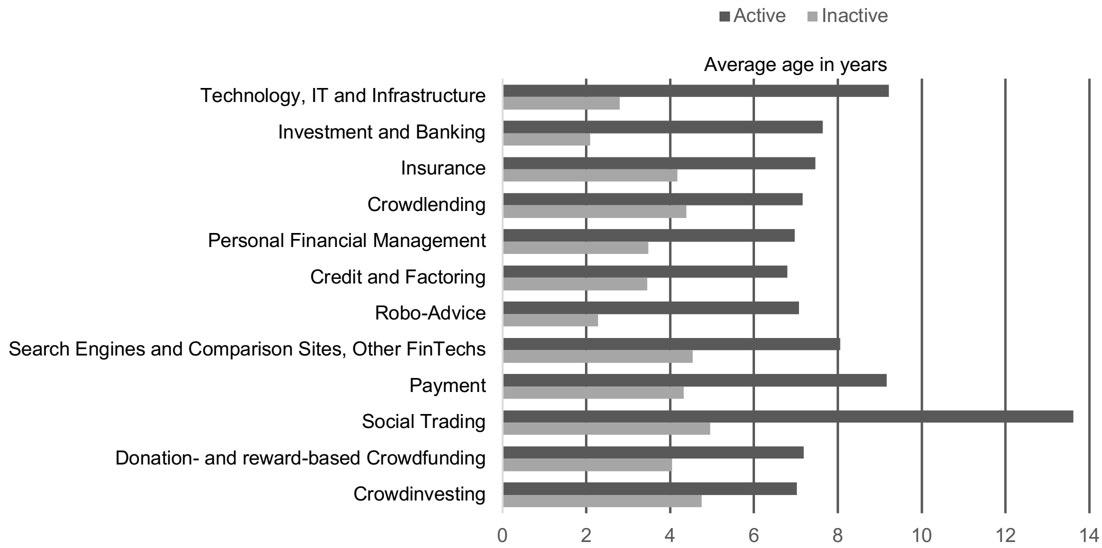



Figure 3.4: Age per subsegment in comparison for active and inactive FinTechs.

et al. (2017), chapter 3, or Dorfleitner et al. (2020). The resulting relative market volume increase of those market leaders is then applied to the total 2020 subsegment figure as published by Dorfleitner and Hornuf (2023) in order to obtain a total market volume estimate for 2021.

Market volumes in all financing subsegments are supposed to represent *transaction volumes*, i.e. money raised, while market volumes in the Asset Management segment are meant to be value of money invested (in the sense of assets under management) by the FinTechs. Both specifications are in line with the mentioned literature, which addresses the same issue for the years before 2021.

Figure 3.5 presents the market volume development over time in the donation- and reward-based crowdfunding subsegment. In reward-based crowdfunding, investors receive a non-monetary consideration from the FinTechs for their financial support of a project which in many cases serves as a pre-financing of the products (Mollick, 2014). This can be of a purely non-material nature, for example in the form of a naming, but can also include material counter-values, such as the delivery of a product to be developed. Even if some platforms define a thematic focus, such as the mediation of regional, sustainable or sports-related projects, the intended use for the collected capital is often very different. Other platforms do not specialize in specific topics. Donation-based crowdfunding is characterized by the fact that the capital providers receive no or, in turn, only an ideal consideration for their financial contribution. Due to the operational overlap between the two subtypes of donation-based and consideration-based crowdfunding, the presentation of market volumes is summarized. While there still is a relative growth of roughly 20 per cent from 2020 to 2021, the absolute figures are still small. Nevertheless, this segment has seen significant growth during the covid-19 pandemic, as many individuals in their local area have supported small businesses, restaurants, bars, and cultural venues with donations. The German market leader which is originally German is the donation-based platform *Betterplace*, followed by *Startnext*, the largest non-original German platform *Kickstarter*, *Viele Schaffen Mehr* and *Indiegogo*.

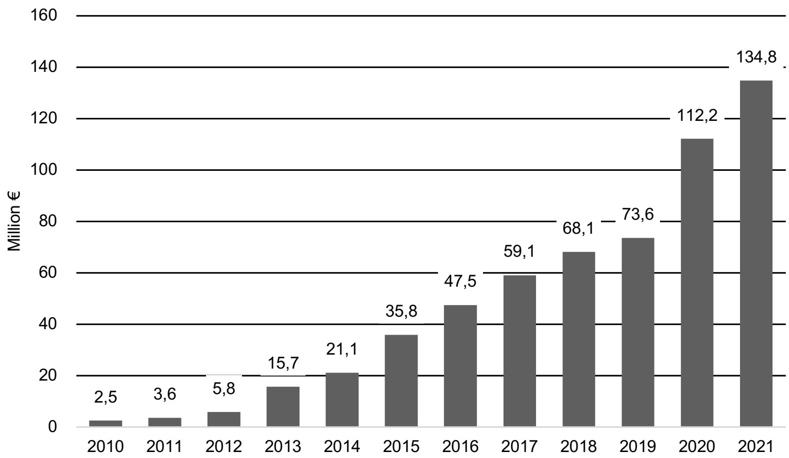



Figure 3.5: Market volumes of the subsegments donation- and reward-based crowdfunding over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

Within the crowdinvesting subsegment, investors often receive an equity-like investment in the form of profit participation rights, dormant equity holdings, participatory loans or subordinated loans. They therefore participate financially in the future development of a company at the end of the term (Hainz et al., 2017, 2019). Note that, unlike in many other countries, in Germany crowdinvesting is not equity-based crowdfunding but rather financing through mezzanine forms such as junior debt. The market volume in the subsegment crowdinvesting (Figure 3.6) has experienced a decline in 2020 because of the covid-19 pandemic, which led to some distortions in the market. However, the crowdinvesting subsegment has recovered and reached an all-time high of 522,3 million EUR in 2021 with a growth rate of 40 per cent with respect to 2020. For crowdinvesting, the German market leader is *Exporo*, followed by *Bergfuerst*, *Companisto*, *Wiwin*, *SeedMatch*, *Zinsbaustein*, *Engel&Völkers*, *EstateGuru* and the non-German platform *Seedrs*.

The segment of crowdlending (Figure 3.7) is characterized by the fact that the capital providers receive predefined annuity payments immediately after financing in exchange for providing the financial resources. Investors and borrowers are either private individuals or companies. FinTechs merely act as intermediaries (Lee and Shin, 2018). The actual lending is handled by a partner bank. After a stagnation phase during the years 2018 until 2020 this segment sees now considerable growth. The market leader is the non-German platform *Loanboox* with approx. 2 billion to which the largest part of the growth in 2021

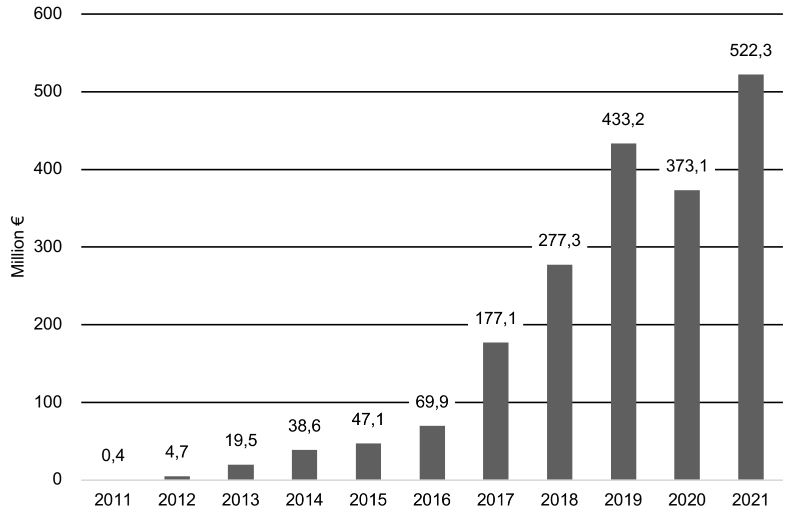



Figure 3.6: Market volume of the subsegment crowdinvesting over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2020 and 2021).

can be attributed, followed by the German platform *Auxmoney*, *Creditshelf* and the Latvian platform *Mintos*.

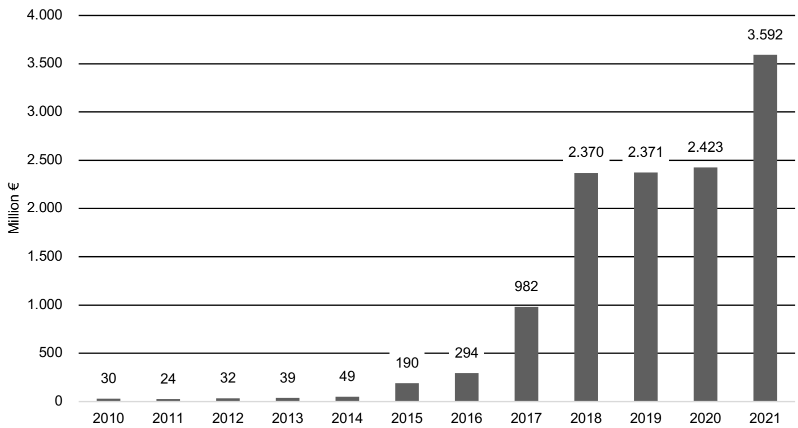



Figure 3.7: Market volume of the subsegment crowdlending over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

Figure 3.8 now shows the aggregate volumes of the crowdlending, crowdinvesting and donation and reward-based crowdfunding segments with 4.249 billion, with crowdlending accounting for both the largest percentage share and the most dynamic growth.

The Credit and Factoring subsegment in Figure 3.9 includes FinTechs that act purely as an online alternative to traditional financing by a bank. Unlike the previous segments, however, the funds are not provided by the crowd. This form of financing is made available to both private individuals and companies (Dorfleitner et al., 2017). Different types of financing can be distinguished, such as traditional loans, online loans, installment loans, express loans or loans for financing the purchase of goods and credit-like factoring. Factoring, in particular,

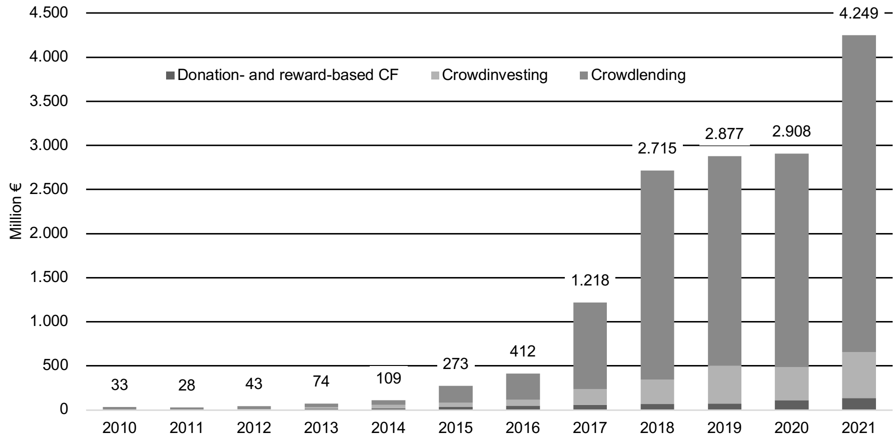



Figure 3.8: Market volume of the segment crowdfunding over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2020 and 2021).

appears to be growing in popularity after being an already large market in which FinTechs provide low entry barriers and funding due to digitization and can take market shares from traditional factoring service providers. The subsegment clearly distinguishes FinTechs from alternative distribution channels of traditional financial intermediaries. If a FinTech is acquired by a bank or no longer operates under its own name, it becomes inactive in our sample. However, we cannot completely rule out the possibility that the FinTech only offers a platform and forwards the volume to traditional financial intermediaries in the background. The largest players on the German market for factoring is *CRX Market* and for credits is *Smava*, followed by *Compeon*, *Aifinyo Factoring* and *Aifinyo Finetrading*.

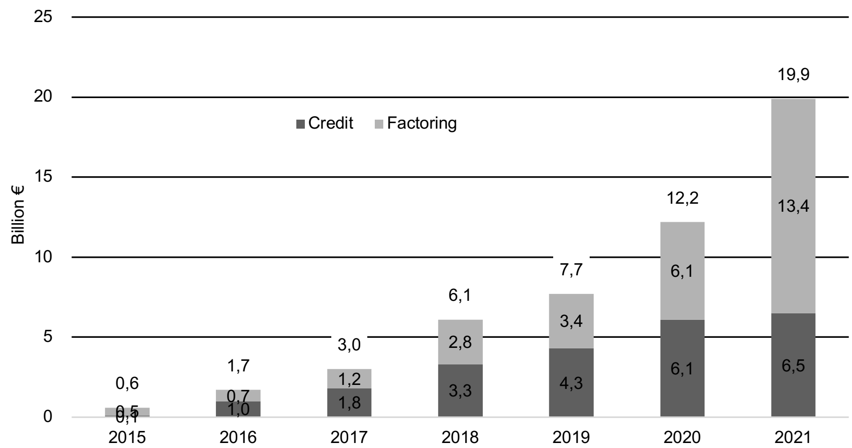



Figure 3.9: Market volume of the subsegment credit and factoring over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

In the investment and banking subsegment, FinTechs focus on traditional banking services such as checking accounts, but typically with more user-friendly functionalities and without cost-driving branch networks. Figure 3.10 shows a linear growth trend over the years reaching a maximum volume of 49.917 million in the year 2021. The largest FinTechs in the subsegment are *Raisin* (in Germany *Weltsparen*), *Deposit Solutions*, *Flaxtex*, *N26* and *Fidor Bank*.

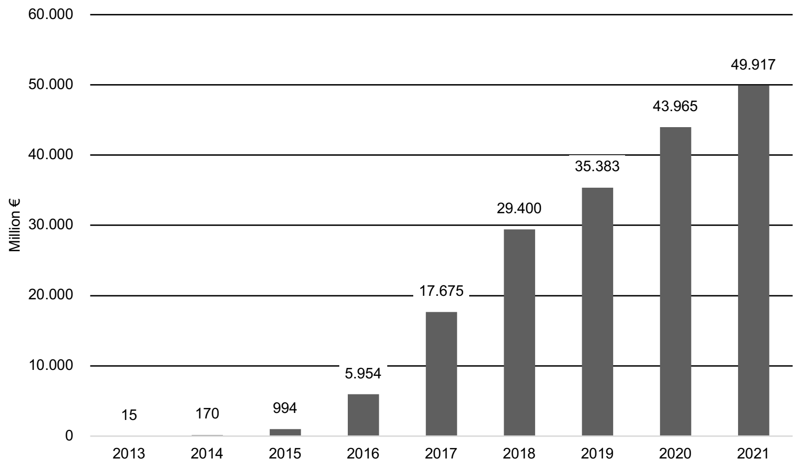



Figure 3.10: Market volume subsegment investment and banking over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

Social trading is a combination of features of online brokers and social networks where a user can follow the trading strategy of another user, which goes so far that the trades can be automatically copied (Glaser and Risius, 2018). The investment strategies use different instruments, such as stocks, exchange-traded funds (ETFs), contracts for difference (CFDs), forex, commodities or cryptocurrencies, depending on the platform. As Figure 3.11 shows, the subsegment of social trading has shown great growth dynamics in recent years. This could be due to the increasing popularity of equity investments in the stock market during the Covid-19 pandemic, as similar dynamics can also be observed in the subsegment robo advice (see Figure 3.12). The market leader on the German market is the Austrian platform *Wikifolio* with a market share of around 75 per cent driving growth and volume in this subsegment, followed by *eToro* and *NagaTrader*.

FinTechs which offer digital and increasingly automated asset management via a platform are assigned to the robo advice subsegment. The personal investment preferences and risk appetite of the investors are taken into account by an algorithm, which allocates the invested capital accordingly. By using robo advisors, investors can achieve diversification effects mostly accompanied by lower volatility and higher returns (D'Acunto et al., 2019). Particularly in the social trading subsegment, we observe the trend towards sustainable investment strategies following the current societal discourse for many robo advice providers. However, one should note that robo advice is a service that even traditional banks are increasingly offering in their online banking, through or without cooperations with FinTechs. As Figure 3.12 shows the assets of German customers managed by robo advisors totaled EUR 10.2 billion at the end of 2021. The German market leader is *Scalable Capital*, followed

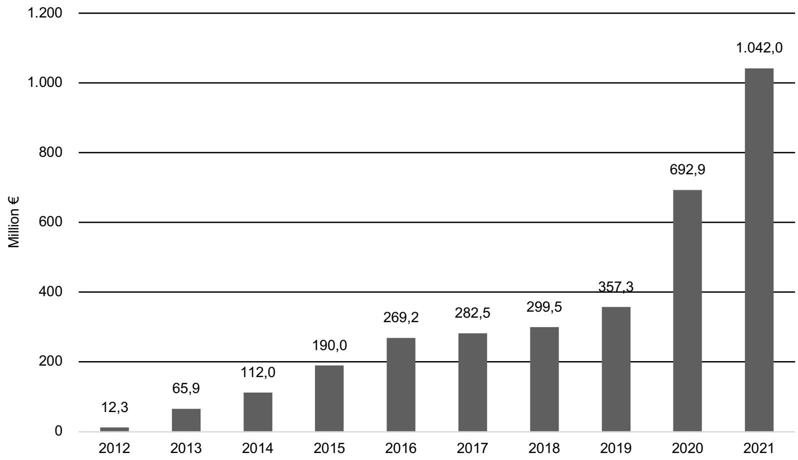



Figure 3.11: Market volume subsegment social trading over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

by *Liqid*, *Quirion* and *Ginmon*.

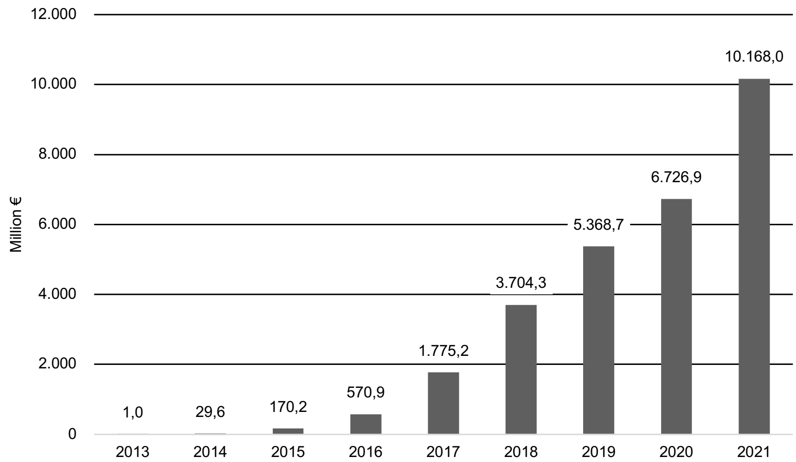



Figure 3.12: Market volume subsegment robo advice over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2021).

To conclude the volume estimates for the year 2021 and the application case of the German FinTech market, we display in Figure 3.13 the sum of the total market volume of the segments financing and asset management over time. We find a steady, linear growth over the years reaching a maximum of 85.3 billion in 2021 in combination with a growth rate of 28 per cent throughout the year 2021. We expect the German FinTech market to establish its position in the market and to further grow. However, the boundaries or demarcation from the traditional banking sector are becoming increasingly blurred in some subsegments due to cooperations or even incorporations with banks.

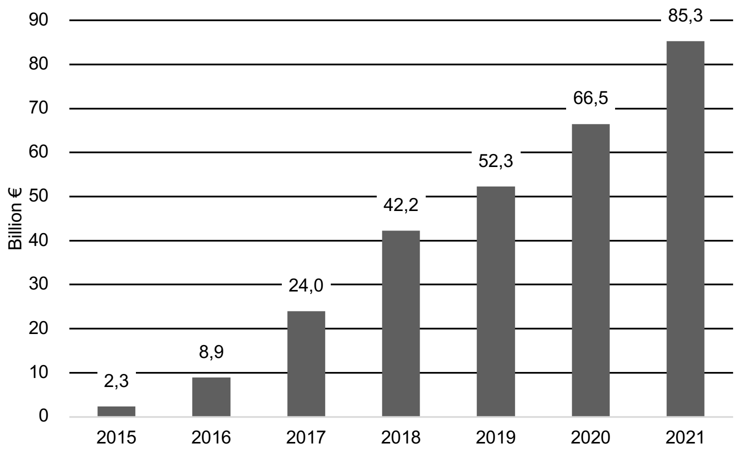



Figure 3.13: Total market volume of the segments financing and asset management over time (Source: Dorfleitner and Hornuf (2023), own calculations for 2020 and 2021).

## 3.4 Conclusion

The dataset presented is suited to perform descriptive analyses to fully comprehend the complete FinTech market in Germany since its emergence. Especially, the dataset is optimal to obtain a historic perspective. Furthermore, the dataset is useful for everybody interested in the dynamic field of financial technology. Therefore, supervisory authorities, academics as well as practitioners, who need an overview, can benefit from the dataset. Moreover, the nature of the dataset enables researchers to perform further cross-sectional analyses. It provides the possibility of longitudinal analyses of the complete market in Germany to observe trends as well as the maturity of this industry sector.

The entries contain further information that can be used for research that is not necessarily only limited to the market in Germany, but related to the entire international FinTech market. Possible concrete research applications are e.g., founder characteristics in network analysis, the origin of the company to account for the geography of start-ups, the operating status as a success indicator as well as for survival analysis.

Additionally, as demonstrated for the year 2021 the total market volumes of particular FinTech segments can be estimated based on the data. While the evidence on the market volumes presented in this report rather was a quick (and necessarily somewhat imprecise) estimate, the next volume investigations should again be based on the whole cross section of FinTechs in Germany. This is a feasible and rewarding (but laborious) task, which due to the freely accessible data set now can be performed by everyone interested in the German FinTech market.

## Acknowledgments

The authors gratefully acknowledge the financial support by the Deutsche Bundesbank. Furthermore, we would like to thank Lars Hornuf, Matthias Schmitt, Lena Wannenmacher and Martina Weber for previous collaboration on this research topic.

# Chapter 4

# Signaling in the Market for Security Tokens

This paper is a joint work with Julia Kreppmeier (University of Regensburg) and has been published as: Kreppmeier, J., Laschinger, R. (2023), Signaling in Market for Security Tokens. *Journal of Business Economics*, 2023, 1–38.

**Abstract** Security token offerings (STOs) are a new means for ventures to raise funding, where digital tokens are issued as regulated investment products on the blockchain. We study market outcomes in the primary and secondary markets for security tokens and examine the associated determinants in the context of signaling theory. We analyze success determinants of 138 STOs and find that a pre-sale and the announcement of token transferability are positively related to the funding success and serve as positive quality signals for investors to overcome information asymmetries. We examine 108 security tokens traded on centralized and decentralized exchanges related to the rapidly evolving area of decentralized finance. There is hardly any underpricing in the market, and it is positively associated with the crypto market sentiment as an external signal. When traded on the secondary market, security tokens generate both extremely positive and negative returns for various short-term time horizons. We disentangle the liquidity situation in the market between centralized and decentralized exchanges and find that decentralized marketplaces are less liquid and offer lower barriers to entry, indicating slow market completion.

**Keywords** Security Token Offering, Blockchain, Signaling, STO, Decentralized Finance

**JEL** G24, K22, L26, M13, O31

## 4.1 Introduction

Advances in digitization and information technology have changed and transformed the financial industry fundamentally. Traditional financial institutions and banks are losing their supremacy as new market entrants and emerging technologies supersede or replace their role as financial intermediaries. Distributed ledger technology (DLT) and the blockchain, as its most common sub-type (Fisch, 2019), enable digitizing any asset class as tokens and are paving the way toward future financial markets. Digital tokens are issued through token offerings on the blockchain, which represent an innovative funding mechanism in entrepreneurial finance. Once the token offering has taken place, the tokens can be traded on the secondary market.

In this study, we examine how signaling affects the behavior of market participants in both the pre-and post-STO phases to provide a holistic picture of the entire market. In particular, we study STO market outcomes such as STO funding success, underpricing, returns, liquidity, and various internal and external signals as determinants. Since the mechanisms and issuance processes are completely different because of blockchain technology, it is worth investigating whether signaling and related theories known from traditional capital markets also apply to the security token market.

The first tokens issued in the year 2013 were utility tokens sold through an initial coin offering (ICO). Utility tokens entail consumption rights for products or services. After a boom period in 2017 and 2018, the initial popularity of ICOs declined because of the lack of investor protection and many fraudulent activities, causing a negative market sentiment (Momtaz et al., 2019). As a result, security tokens issued through security token offerings (STOs) have since emerged as innovative investment products (Lambert et al., 2022). Security tokens represent shares of ownership in corporate equity, fixed income, investment funds, commodities, or less liquid asset classes such as real estate or fine art. Due to the classification as conventional securities and the resulting regulatory requirements, they are considered the regulatory-compliant successors to utility tokens. This new form of venture financing has several advantages: companies can easily reach a large investor base while reducing transaction costs. Moreover, clearing and settlement occur quickly, and at any time, transparency regarding the transactions is achieved through the blockchain, and fractionalization enables investments in less liquid asset classes with high entry barriers (Ante and Fiedler, 2020; Lambert et al., 2022). The interoperability of the blockchain could solve the previous problem of lack of compatibility between different systems or databases and theoretically enables self-custody of any tokenized asset on one platform (Momtaz, 2023). Another major advantage of STOs is the potential liquidity provided through the possibility to transfer and trade tokens on secondary markets. As a result, security tokens combine the benefits of the underlying technology with the legal protection of conventional securities.

Prior studies on ICOs analyzed success determinants (Adhami et al., 2018; Amsden and Schweizer, 2019; Fisch, 2019; Howell et al., 2020; Roosenboom et al., 2020), investor characteristics and motives (Boreiko and Risteski, 2021; Fahlenbrach and Frattaroli, 2021; Fisch et al., 2021; Hackober and Bock, 2021) or the informative disclosure and language of white papers (Florysiak and Schandlbauer, 2022; Thewissen et al., 2022). Other studies emphasize the post-ICO performance of tokens, such as underpricing (Chanson et al., 2018; Felix and von Eije, 2019) and/or short-term returns (Benedetti and Kostovetsky, 2021; Fisch and Momtaz, 2020; Lyandres et al., 2022; Momtaz, 2021a). However, due to the security and regulation characteristics and the associated rights and obligations for companies and investors alike, security tokens need to be considered on their own. The existing literature on STOs studies success determinants during the funding process regarding investors' rights, issuer, and offering characteristics (Lambert et al., 2022) or cheap human capital and social media signals (Ante and Fiedler, 2020). Momtaz (2023) describes the economics, law, and technology of STOs and provides a comparison of STOs, ICOs, and IEOs. Other studies embed STOs in a theoretical context, e.g., Gan et al. (2021) study the optimal design of an STO, Gryglewicz et al. (2021) examine when token financing is preferable to equity financing, while Miglo (2021) compares STOs and ICOs under moral hazard and demand uncertainty.

We theoretically embed this article in the context of signaling theory to overcome information asymmetries between the STO-issuing company and potential primary and secondary market investors both during the pre-and post-STO phase. This article extends previous research by investigating whether a pre-sale and the announcement of token transferability or later expected liquidity are positively related to the success of an STO. They can be interpreted as positive quality signals and have not been investigated in the context of an STO yet. During a pre-sale, the transparent investment of publicly known experts and institutions serves as a signal for trustworthiness (Howell et al., 2020) and constitutes a method to gather valuation-relevant information at an early point of the process to make the main funding more effective (Momtaz, 2020). We find that a pre-sale and the announcement of transferability serve as quality signals, and both have a positive link to the funding success of an STO. The announcement of future token transferability enables the investors to trade the tokens on secondary marketplaces and translates into liquidity in the post-STO phase. Once trading begins, the market valuation should lead to accurate pricing and show whether the signals previously sent about the quality of the STO correspond to reality (Florysiak and Schandlbauer, 2022). In this regard, to the best of our knowledge, we are the first to empirically investigate the post-STO phase by analyzing the secondary market for security tokens. As the first market valuation, we study underpricing and relate it to the literature on IPOs regarding determinants such as market sentiment and large investors. Underpricing hardly seems to exist in the STO market, which is related to the market sentiment as an external signal. As a further market valuation, we examine the short-term post-listing performance by calculating buy-and-hold as well as buy-and-hold abnormal returns over different short-term horizons. In this way, we can verify whether the signals previously sent reflect the reality of the quality of the STO and translate into higher returns. We find that both extremely negative and positive returns can be achieved depending on the time horizon. Furthermore, we analyze the evolution of the liquidity situation in the market since its inception. In particular, we add to the literature the substream of research that disentangles the effect of a token being traded on centralized or decentralized exchanges as a means of the rapidly evolving area of decentralized finance. So far, this has solely been elaborated for cryptocurrencies as a whole by Aspris et al. (2021) but has not been addressed in any other previous study on the aftermarket performance of tokens. Our study is based on two hand-collected, overlapping, but non-identical datasets comprising 138 STOs and 108 security tokens traded on the secondary market.

The remainder of this paper is organized as follows. In Section 4.2, we present the technological background and classification of STOs. In Section 4.3, we present an overview of signaling theory and derive our hypotheses. Section 4.4 describes data, variables, and results regarding the pre-STO phase and the analysis of STO success determinants. Section 4.5 focuses on the post-STO phase, including STO underpricing, returns to investors, and liquidity. Section 4.6 concludes this study.

## 4.2 Security token offerings: Background

### 4.2.1 Technological background

We first describe the technological background and termini relevant to a security token offering on the distributed ledger technology. DLT refers to an approach in which data is recorded and shared via a decentralized, distributed ledger of various different participants. The blockchain is the most relevant form and sub-category of DLT, although both terms technically are not identical (Fisch, 2019). However, we use the terms synonymously in this study. The structure in the form of cryptographic chains of data blocks is characteristic of blockchains. Anyone can see and download a copy of a public blockchain. The only relevant version is the one that contains the latest legitimate transactions (Schär and Berentsen, 2020). The immutability of the blockchain and its transactions generate trust between the parties involved (Chod et al., 2022). Ethereum is the most commonly used blockchain infrastructure for ICOs (Howell et al., 2020) as well as for STOs. This has prevailed due to the wide range of application possibilities regarding the programming and execution of smart contracts. Smart contracts are digital contracts that allow specific transactions to be executed automatically when certain predefined events occur (Buterin, 2013). The addition of assets to the blockchain is referred to as tokenization, while the digital version of the asset on the blockchain is called a token (Schär, 2021). The financial use case for smart contracts is these digital tokens, where the smart contract verifies, for example, that the investor has received payment and then automatically sends the token to the investor's wallet (Cong et al., 2022). The distinction between the three following types of tokens has crystallized (Howell et al., 2020), though there are several hybrid forms. Payment tokens are a means of payment for purchasing goods or services (e.g. Bitcoin). Utility tokens entail consumptive rights to use blockchain-based services and security tokens. For security tokens, we apply the definition of Lambert et al. (2022) as "a digital representation of an investment product, recorded on a distributed ledger, subject to regulation under securities laws" (Lambert et al., 2022, p. 302). The application of blockchain to the entire financial sector holds great potential for systemic change (Guo and Liang, 2016; Wright and De Filippi, 2015).

### 4.2.2 Implications for financial markets

The digitization of assets has multiple implications for investors, companies, and financial markets alike. The global nature of the blockchain, and thus the lower barriers between financial markets of different countries, means companies have a wider geographic scope and can reach a broader investor base (Chang, 2020). Fractional ownership through the divisibility of the underlying asset enables retail investors to invest small amounts of money in previously unattainable asset classes, which allows investors to diversify their portfolios more broadly (Kreppmeier et al., 2023). Investors no longer need to demand higher returns resulting from higher divestment risk. Therefore, digitized assets can reduce illiquidity premia and finally make these assets trade closer to their fair value (OECD, 2020). The properties of the blockchain promise increased transparency in tamper-proof, instantaneous transactions. Automated transaction processing, as well as the allocation and distribution of payment flows using smart contracts, can reduce the costs of issuance and transactions (Chang, 2020; Guo and Liang, 2016). Automated settlement and disintermediation lead to a reduction in trading fees and a significant decrease in settlement times, thereby enabling more efficient financial markets (Momtaz, 2023). Moreover, by leveraging a blockchain, the counterparty risk can be eliminated since intermediaries become obsolete (Uzsoki, 2019). All of these technical innovations are paving the way for a digitized token economy of the future.

### 4.2.3 Differentiation from existing forms of financing

IPOs are the traditional, regulation-compliant way to list a company publicly for the first time. A common feature of IPOs and STOs is that the offering has to comply with regulations, and investors receive binding rights. A substantial difference between STOs compared to IPOs is the use of a blockchain. This ensures that the settlement of the transactions after an STO is faster and more efficient (Mills et al., 2016). The issuance and marketing processes of IPOs and blockchain-based offerings are completely different: IPOs perform a book-building process and use social media solely to attract investors; token offerings communicate relevant financing information for the offering to prospective investors through social media channels (Ofir and Sadeh, 2020).

The basic idea behind crowdfunding (CF) is that funding of a target amount is achieved by collecting small amounts of money from the crowd of investors – this is a common feature with STOs because of fractionalization. For CF, platforms handle the projects holistically, act as intermediaries, and perceive monitoring functions in the selection process of the projects. In ICOs or STOs, platforms play only a subordinate role in displaying aggregated information about projects due to the blockchain, leading to a shift in screening activities exclusively to individual investors (Block et al., 2020). The problem with CF is that the shares purchased may be difficult to resell or liquidate because there is no real secondary market, while tokens can usually be traded on secondary markets.

Both CFs and ICOs are about raising money from potential users to spend later on the platform for services, outside of which the token has no value (Howell et al., 2020). Thus, utility tokens are legally classified only as donations with limited rights, while investors in regulated security tokens receive corresponding rights from the underlying financial instrument (Ante and Fiedler, 2020).

## 4.3 Theory and Hypotheses

### 4.3.1 Signaling theory

The conceptual framework of our hypotheses draws upon the literature in the field of information asymmetries and signaling. Signaling theory deals with reducing information asymmetries between the involved parties (Spence, 2002). In the case of STOs, these information asymmetries arise because the STO-issuing firm has internal, private information about its quality and future prospects that is not available to the public. The signal itself must be observable for the receiver and associated with monetary, time, reputation, or effort-related costs that prevent imitation (Connelly et al., 2011). Therefore, companies are incentivized to communicate this information to potential investors and reduce information asymmetries. As a result, investors are better able to identify high-quality ventures and invest accordingly (Bergh et al., 2014; Florysiak and Schandlbauer, 2022). Information asymmetries are especially prevalent in token offerings, as these companies are often young and lack a solid track record and experience (Howell et al., 2020). This effect is amplified by retail investors, who are mainly present in the market for token offerings (Lee et al., 2022). In comparison to institutional investors, retail investors have less experience and financial resources to evaluate investment opportunities (Ahlers et al., 2015). Additionally, the underlying blockchain requires investors to have a certain level of technical knowledge and familiarity (Momtaz, 2021a). Consequently, it is crucial for companies conducting an STO to send quality signals to potential investors in order to reduce information asymmetries. Information asymmetries and the related signaling play an important role both during the STO on the primary market (the pre-STO phase) and when security tokens are traded in the secondary market (the post-STO phase).

### 4.3.2 Hypotheses Development: Pre-STO phase

An STO consists of several rounds, and a pre-sale can precede the actual main public offer. A pre-sale commonly aims at a limited group of investors and has several advantages. On the one hand, Howell et al. (2020) compare a pre-sale to the book-building process in IPOs to ascertain information about the correct demand and price, which makes the main funding more effective (Momtaz, 2020). Usually, a pre-sale has a discount on the token price for early investors. A pre-sale could therefore lead to early participation and a momentum effect (Roosenboom et al., 2020) due to the authentication of the issuer, especially when prominent experts or institutions can be attracted (Howell et al., 2020). In the context of reward-based and equity crowdfunding, it is found that the generation of early investors and an early, strong campaign is a quality signal of project success for potential investors (Colombo et al., 2015; Vulkan et al., 2016). The possibility of costly gathering price-relevant information and attracting early attention before the main offering could signal that the STO is of high quality, which may be perceived as positive by investors.

> **Hypothesis 1:** *The implementation of a pre-sale phase is positively related to the success of an STO.*

There are two ways to trade and transfer a security token: on exchange platforms or directly from peer-to-peer (P2P). Even if a security token is not listed on an exchange platform, an investor can generate liquidity via a P2P transaction. The transferability of the token is constitutive of the possibility of obtaining future liquidity by trading the security token. From a technical standpoint, the feature of transferability of a token cannot be taken for granted. Some companies point out that the issued token may not be transferred and that the transferability will therefore be technically restricted over the course of programming the token.[1] This technical limitation restricts the future liquidity of the token. Florysiak and Schandlbauer (2022) even go so far as to claim that a security token gets its value from the fact that it is tradable. Already in the ICO context, it is stated that technical aspects of the technology used, such as the transferability of the token, play a major role in the investment decision of an investor (Fisch et al., 2021). Transferability is a major advantage of STOs over crowdfunding. For equity crowdfunding, a platform is explicitly required to trade the shares due to the lack of a blockchain (Signori and Vismara, 2018). Investors could therefore rate the announcement of transferability of the security token as a quality signal and invest primarily in STOs in which they can resell the security token without restrictions from the issuing company to generate future liquidity. The explicit emphasis on the intent of transferability is a potential indicator of high-quality STOs and shows that they intend to trade their tokens in the secondary market in the future, thus deriving value.

> **Hypothesis 2:** *The announcement of transferability is positively related to the success of an STO.*

Transferability is both a quality signal during the pre-STO phase and a technical prerequisite for tokens to be traded on the secondary market in the post-STO phase. The market valuation in the post-STO phase can be used to verify to what extent the signals sent during the STO correspond to reality and are subsequently reflected in the associated STO market outcomes.

### 4.3.3 Hypotheses Development: Post-STO phase

In the following, we focus on the post-STO phase by investigating underpricing or, more specifically, 'money left on the table' for the issuer (Loughran and Ritter, 2002). We account for underpricing as the return of an STO investor on the primary market who holds the token until the listing on the secondary market. We derive hypotheses for the determinants of STO underpricing that relate to external signals, in other words, the signals that come from outside the STO-issuing firm as opposed to the pre-STO phase.

In the *increased monitoring hypothesis*, Stoughton and Zechner (1998) state that underpricing is a way to attract large investors under the assumption that only these investors are capable of monitoring. In practice, companies seek to incorporate large investors into the shareholder structure who have mechanisms to monitor and influence management in order to increase the firm value in the interests of all shareholders (Admati et al., 1994).

[1] Vermögensanlagen-Informationsblatt RAAY Real Estate GmbH, 2020: "Investors do not have the right to transfer and encumber the token to third parties. An obligation of the issuer or the company to take back the token exists through the right of termination.[...] A sale of the token by the investor is generally not possible." [translation by the authors]

Stoughton and Zechner (1998) state that small investors free-ride on large investors' monitoring, an agency-problem which is also documented in the context of equity crowdfunding (Hornuf and Schwienbacher, 2018; Moritz et al., 2015). Therefore to increase the firm value, the company needs to lure large investors with the help of underpricing in their own interest. As a consequence, the fewer large investors invested in the STO, the primary offering, the more pronounced the underpricing will be to incentivize large investors to invest in the secondary market.

**Hypothesis 3:** *The number of large investors during the STO is negatively related to underpricing.*

The IPO literature suggests that market sentiment is an important predictor of underpricing (Loughran and Ritter, 2002; Green and Hwang, 2012). The demand of sentiment investors may disappear in times of negative market sentiment, and, therefore, 'normal' investors with IPO stocks in inventory need to be compensated through underpricing for the associated risk of losses (Ljungqvist et al., 2006). We expect that the market for security tokens is salient to this kind of market timing since Baker and Wurgler (2006) have shown that investor sentiment is particularly present for subjective and difficult-to-arbitrage securities, such as security tokens. It is up to the STO-issuing firm when exactly the trading of their tokens on the secondary markets starts. In order to prevent their token from generating negative initial returns, they will time the first trading day and avoid phases of negative market sentiment (Drobetz et al., 2019). Consequently, we assume that issuers await times of positive market sentiment and avoid negative market sentiment as an external signal, which increases underpricing.

**Hypothesis 4:** *The market sentiment is positively related to underpricing.*

## 4.4 Pre-STO phase

### 4.4.1 Sample construction and data of STO success determinants analysis

There is no central database of all STOs carried out to date. As such, this sample is obtained by manually collecting and matching data from multiple data sources and websites. First, the starting point was the website *Digital Asset Network*. From there, we moved to various aggregator sites and looked for offers declared as STO.[2] In the second step, we searched the companies' websites for information about each STO. For STOs

[2]The aggregator websites considered in this study are Block Databank, Blockdata, BlockState, CoinMarketPlus, Digital Asset Network, ICO Bench, ICO Drops, ICO Holder, ICO Stamp, ICOs Bull, STO Analytics, STO Docket, STO Filter, STO Market, STO Rating, STO Scope, The Tokenizer.

issued in the USA, we additionally accessed the *EDGAR* database from the SEC. We collected documents such as white papers, legal documents, prospectus, and further investor documents. Third, a plausibility check took place to verify the collected data, including matching with transaction data from the blockchain, as information in different databases may converge. The final step for each observation was to check the accordance with the definition of a security token of Lambert et al. (2022). We had to exclude many STOs due to limited data availability, STOs that were announced but for which there was never an offer and offerings that did not meet the definition. We executed these steps in sequence and obtain 71 STOs with very detailed data. We validated and complemented our self-collected data with 67 STOs from the *Token Offerings Research Database* (TORD) of Momtaz (2021b) after removing duplicates and follow-up research. Finally, we end up with 138 STOs. These STOs were issued between 1st March 2017 and 31st December 2020. The sample size in other STO success determinants studies is similar, especially the reduction due to missing detailed information to perform the multivariate analysis (Ante and Fiedler, 2020; Lambert et al., 2022).

### 4.4.2 Variables of STO success determinants analysis

The choice of the dependent variable to measure STO success is not completely trivial. In pure equity markets, naturally, a valuation-based measure is preferable, which relates the amount raised to the portion of equity sold by the issuer. For instance, two companies may raise the same amount of money in the STO but give up a different proportion of equity, resulting in different valuations. However, in addition to stocks, our sample also includes fund or debt tokens, whose observations we do not want to lose by opting for a valuation-based variable since the focus of this study is on new entrepreneurial funding mechanisms in general and not on the type of capital. Therefore, the *Funding Amount* serves as our simplified dependent variable reflecting a firm's overall ability to raise funds from investors and is thus the most direct way to gauge a firm's access to external finance (An et al., 2019). The use of the variable to quantify the success of a project is common in the literature on venture capital (Baum and Silverman, 2004), crowdfunding (Block et al., 2018; Mollick, 2014), ICOs (Fisch, 2019; Lyandres et al., 2022), and STOs (Ante and Fiedler, 2020; Lambert et al., 2022). Accordingly, our results need to be interpreted from the investors' perspective, as they reflect the collective reaction of investors to the STO rather than the financial corporate valuation or implications thereof. To account for the high skewness of the *Funding amount*, we use a log transformation. As an alternative measure of success, we incorporate the variable *Funding amount to target* as an additional dependent variable. It is the percentage ratio of the *Funding amount* to the *Hardcap*, the pre-defined target amount of the STO. Considering this ratio allows us to address the issue that a few STOs with large *Funding amounts* may bias our results (Lambert et al., 2022).

To test Hypothesis 1, we include the dummy-variable *Pre-sale*, which takes a value of 1 if a firm conducts a *Pre-sale* phase before the main funding, and 0 otherwise. To test Hypothesis 2, we consider the dummy-variable *Transferability*, which accounts for whether a company announces in its published documents for the STO that the token is technically equipped to be transferable for investors.[3]

We include several control variables in our models. We control for different types and rights of tokens representing their economic purpose: *Equity token*, *Fund token*, and the remaining investment tokens. *Equity tokens* usually entail the investor with cashflows in the form of dividend payments. *Fund Tokens* offer diversification opportunities through indirect investments, which makes them potentially attractive to investors. Additionally, the dummy-variable *Voting rights* refers to the possibility of the investor to participate, e.g., in the composition of the board or in structural decisions that provide the investor with opportunities for control. If STO investors are not entitled to a *Voting right*, it would indicate the typical corporate governance issue of separation between control rights and ownership (Lambert et al., 2022). We further control for several variables which are known from CF and ICOs. The dummy-variable *Softcap use* indicates whether a minimum funding threshold must be reached for an STO to be issued. The metric variable *Hardcap* measures the STOs' funding target for which a log transformation is used to account for the skewness. Investors have an incentive to select projects with realistic *Hardcaps*. A target amount set too high could indicate that the project will not reach the amount. A target amount that is too low could suggest that a project will not be carried out (Mollick, 2014) or that a campaign will stop early (Fisch, 2019). The variable *Telegram* describes whether a company makes use of Telegram as a communication medium. *Telegram* has established itself as a communication channel in the crypto world to communicate information directly with potential investors. The use of *Telegram* signals a company's familiarity with the crypto sphere (Amsden and Schweizer, 2019). We additionally include variables related to the characteristics of the issuing company, as investors draw inferences about the quality of the offering from the firm. The variable *Listing* indicates whether an STO-executing firm is listed on a traditional stock exchange, which is a signal for the potential maturity and regulatory compliance of the company. We additionally control for the logarithmized *Age* of the company as the difference between the date of STO and the date of formation of the firm. The probability of a company's survival decreases more significantly in earlier years (Pazos, 2019). Investors could anticipate this and invest in older companies. Already in the crowdfunding context, the influence of geography on campaign success was identified (Mollick, 2014). Because of this, additional dummy variables for the country of incorporation are included: *USA*, *Cayman Islands*, *UK*, *Europe*, and the

[3] While an investor could also glean this information from the smart contract, it cannot be assumed that the average investor has these technical capabilities. Therefore, we rely on the information provided in the offering documents.

remaining countries.

### 4.4.3 Descriptive statistics of STO success determinants analysis

We report the descriptive statistics of the variables used in the analysis for STO success determinants in Table 4.1.

Table 4.1: Descriptive statistics for STO success determinants.

| Statistic | N | Mean | SD | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Dependent variables* | | | | | | | | |
| Funding amount | 138 | 9.698 | 6.917 | 0.000 | 0.000 | 13.220 | 14.871 | 18.713 |
| Funding amount to target | 71 | 0.311 | 0.401 | 0.000 | 0.0001 | 0.120 | 0.524 | 1.070 |
| *Independent variables* | | | | | | | | |
| Pre-sale | 138 | 0.377 | 0.486 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| Transferability | 71 | 0.831 | 0.377 | 0.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Equity token | 71 | 0.366 | 0.485 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| Fund token | 71 | 0.113 | 0.318 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| Voting rights | 71 | 0.183 | 0.390 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| Softcap use | 71 | 0.662 | 0.476 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| Hardcap | 71 | 8.433 | 8.328 | 0.000 | 0.000 | 13.883 | 16.660 | 20.723 |
| Telegram | 71 | 0.563 | 0.499 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| Listing | 71 | 0.056 | 0.232 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| Age | 71 | 0.557 | 0.722 | 0.000 | 0.000 | 0.164 | 0.895 | 3.088 |
| Cayman Islands | 138 | 0.051 | 0.220 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| Europe | 138 | 0.297 | 0.459 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| UK | 138 | 0.087 | 0.283 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| USA | 138 | 0.312 | 0.465 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |

*Note:* This table reports the descriptive statistics (mean, standard deviation, minimum, $25^{th}$ percentile, median, $75^{th}$ percentile, and maximum) for the full sample. The different number of observations of N=71 and N=138 is based on the fact that not all of the variables considered in our analysis are included in the *Token Offerings Research Database* of Momtaz (2021b). All variables are defined in Table 4.8.

The *Funding amount* has a mean of 9.698 corresponding to $16,285. The minimum and 25th percentile with a value of 0 indicate that there are many unsuccessful offerings. The maximum value of 18.713, which corresponds to $133,953,060, demonstrates the high skewness. The mean and median of the alternative success variable *Funding amount to target* reveal that the majority of companies do not reach the *Hardcap*. *Pre-sales* were conducted on average of 37.7% of the ventures to offer their tokens prior to the main funding phase. The share of companies offering a *Pre-sale* is lower in comparison to ICO studies (Howell et al., 2020; Florysiak and Schandlbauer, 2022; Fisch, 2019). The *Transferability* feature of the token to ensure future liquidity was mentioned by 83.1% of the ventures in their offering documents.

Our control variables regarding token types and rights show that most STOs with 36.6% issue an *Equity token* entailing dividend payments and 11.3% a *Fund token* as an indirect investment. A share of 18.3% of the tokens provides a *Voting right* to the investor, which is an indication of the separation of control and voting rights. The issuers do not intend to give investors a say in the company matters, which is consistent with the findings of Lambert et al. (2022). The control variables related to modern forms of venture funding reveal that 66.2% of the companies make use of a *Softcap* as a financing threshold. The *Hardcap* with a median of 13.883 corresponding to $1,069,819 and a maximum of 20.723 which corresponds to $999,734,198, both of which are higher than the actual *Funding amount*, indicate that most companies fail to meet their pre-specified *Hardcap*. On average, the mass-market communication channel *Telegram* is used by 56.3% of companies to communicate directly with investors. Table 4.9 in the Appendix displays the correlation coefficients for all variables related to the analysis of STO success. The variance inflation factors (VIF) are reported below the regression coefficients in Table 4.2. We have neither high correlations above 0.5 nor VIFs above a conservative threshold of 5. Thus, we assume that multicollinearity is no concern in our analysis.

### 4.4.4 Multivariate Analysis: STO success determinants

Table 4.2 presents the results of the tobit models with *Funding amount* as the dependent variable. We estimate a tobit specification as the dependent variable *Funding amount* is left-censored at zero since we account for unsuccessful funding with a value of zero. All specifications are estimated with heteroscedasticity-robust standard errors and year dummies. Model (1) includes the STOs of the *TORD* of Momtaz (2021b) resulting in 138 observations, while models (2) to (5) are reduced to the smaller sample of 71 observations with more detailed data because not all of the variables in our analysis are in the *TORD* database. However, the coefficients continue to have the same signs and similar significances. The hypotheses-related variables are included interchangeably and step-wise in the models (2) to (4). In the full model (5), company-specific variables are also considered. The following explanations refer to the full model (5) with a Pseudo $R^2$ of 0.129. The relation of the number of observations to the number of variables in our models could be suspicious for overfitting. Therefore, we additionally calculate the Akaike Information Criterion (AIC). We find that our full model (5) has the lowest AIC value compared to the other models, thus, it is the best-fit model for our data.

Model (5) in Table 4.2 shows that conducting a *Pre-sale* is positively associated with the *Funding amount*. The occurrence of a *Pre-sale*, indicated by the dummy-variable with a value of 1, equals a c.p. increase of 16,204% in the *Funding amount*.[4] This result is important for STO-issuing companies since it emphasizes that the course for a successful

[4]Since the dependent variable *Funding amount* is logarithmized, we have a log-level model. We, therefore, apply the Halvorsen and Palmquist (1980) correction for an exact interpretation of the economic significance, i.e., for *Pre-sale*: $100(e^{\beta_1} - 1)\% = 100(e^{5.094} - 1)\% = 16,204\%$.

Table 4.2: Tobit STO success determinants analysis.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Funding amount | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Pre-sale | 3.100** | 4.970** | | 5.538** | 5.094** |
| | (1.563) | (2.320) | | (2.155) | (2.216) |
| Transferability | | | 4.232** | 5.018*** | 5.858*** |
| | | | (1.770) | (1.761) | (1.676) |
| Cayman Islands | 9.720*** | 13.128*** | 11.192*** | 11.877*** | 12.839** |
| | (2.463) | (4.229) | (3.147) | (4.083) | (4.480) |
| Europe | 6.589*** | 4.683 | 4.060 | 3.111 | 3.064 |
| | (2.269) | (2.990) | (2.733) | (2.806) | (2.764) |
| UK | 3.678 | 3.775 | 4.988 | 4.214 | 5.150 |
| | (3.545) | (3.733) | (3.130) | (3.395) | (3.189) |
| USA | 3.241 | -0.023 | 0.294 | -0.677 | -0.893 |
| | (2.335) | (3.016) | (2.684) | (2.726) | (2.839) |
| Equity token | | 2.019 | 1.697 | 1.784 | 1.714 |
| | | (1.699) | (1.690) | (1.596) | (1.487) |
| Fund token | | 3.123 | 3.316 | 1.650 | 1.848 |
| | | (3.327) | (3.358) | (3.076) | (3.172) |
| Voting rights | | 2.854* | 3.787** | 3.022* | 3.383** |
| | | (1.705) | (1.736) | (1.556) | (1.517) |
| Softcap use | | −4.896*** | −5.173*** | −5.216*** | −5.460*** |
| | | (1.357) | (1.326) | (1.279) | (1.223) |
| Hardcap | | −0.288 | 0.022 | -0.228 | -0.025 |
| | | (0.483) | (0.469) | (0.455) | (0.450) |
| Telegram | | −7.116*** | −5.423*** | −8.132*** | −8.252*** |
| | | (2.113) | (1.675) | (1.914) | (1.900) |
| Listing | | | | | 4.920 |
| | | | | | (3.694) |
| Age | | | | | 1.320 |
| | | | | | (1.025) |
| Mean VIF | 1.170 | 1.553 | 1.466 | 1.571 | 1.591 |
| Maximum VIF | 1.237 | 1.963 | 2.099 | 2.186 | 2.078 |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 138 | 71 | 71 | 71 | 71 |
| Pseudo $R^2$ | 0.047 | 0.101 | 0.095 | 0.116 | 0.129 |
| Log pseudolikelihood | −373.305 | −189.648 | −190.956 | −186.322 | −183.715 |
| AIC | | 409.236 | 411.912 | 404.645 | 403.431 |

*Note:* This table reports cross-sectional Tobit regressions. The reference category for the countries is *Country other*. All models include a not reported constant. Heteroscedasticity-robust standard errors in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table 4.8.

STO can be set early on by planning the individual STO phases, including a *Pre-sale*. According to the rationale of signaling theory, conducting a *Pre-sale* involves effort and costs for the STO and is therefore translated into higher signaling costs which only high-quality STOs can afford. Likewise, however, it is an easy-to-observe signal to potential investors that issuers are bearing these costs and are trying to gather valuation-relevant information to make the following main sale more effective. Consequently, we find empirical support for Hypothesis 1.

Moreover, the coefficient of *Transferability* is positive and significant. The announcement of *Transferability* in the offering documents, indicated by the dummy-variable with a value of 1, equals a c.p. increase of 34,902% in the *Funding amount*. This finding underpins that the announcement of *Transferability* and the expectation of future liquidity enables companies to raise more funding. We find supportive evidence for Hypothesis 2 regarding the positive signaling effect of the announcement of *Transferability* to overcome information asymmetries. Interestingly, when embedding the results in the context of signaling, we observe that a company's intention to offer a transferable security token is crucially related to the success of an STO, even though it does not come at a high cost for the issuer and cannot be easily verified by investors. This may be due to the fact that the expectation to trade the token in the future appears to be the main motive for a token investment (Fisch et al., 2021).

The results pertaining to the token type and rights deliver only for *Voting rights* a positive and significant link to the *Funding amount*. This means that, unlike IPOs (Smart et al., 2008) and equity crowdfunding (Cumming et al., 2019), the separation of ownership and control does not play a major role for STOs. This result is in line with Lambert et al. (2022), who claim that the transparency of the blockchain and the associated lower costs of acquiring information for external investors reduce this agency problem. The coefficient of the variable *Softcap use* is negative and significant. Lambert et al. (2022) argue that if a *Softcap* is used, a company needs to convince more investors to reach the financing threshold in the first place. The utilization of *Telegram* as a communication channel to investors is negatively related to the success of an STO. Lyandres et al. (2022) claim that social media signals depend on the quality and cost of the social media platform, which is in the case of *Telegram* low. The *Cayman Islands* are positively associated with the *Funding amount*. However, we cannot disentangle the real considerations of the companies in this regard. On the one hand, the *Cayman Islands* are considered a tax haven with numerous tax advantages for investors, and on the other hand, they offer a more lax legal framework. For the remaining company-specific variables, we do not find a significant coefficient in any model specification.

As a robustness check displayed in Table 4.3, we estimate the tobit models with the alternative success measure *Funding amount to target* as the dependent variable.

Table 4.3: Robustness: Alternative success variable.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Funding amount to target | | |
| | (1) | (2) | (3) |
| Pre-sale | 0.160 | | 0.167 |
| | (0.150) | | (0.138) |
| Transferability | | 0.303*** | 0.406*** |
| | | (0.109) | (0.109) |
| Cayman Islands | 0.665** | 0.555* | 0.655* |
| | (0.327) | (0.288) | (0.339) |
| Europe | 0.235 | 0.167 | 0.135 |
| | (0.166) | (0.153) | (0.169) |
| UK | 0.095 | 0.126 | 0.176 |
| | (0.191) | (0.169) | (0.178) |
| USA | −0.002 | −0.008 | −0.063 |
| | (0.171) | (0.158) | (0.168) |
| Equity token | 0.071 | 0.060 | 0.061 |
| | (0.110) | (0.103) | (0.094) |
| Fund token | 0.014 | -0.010 | -0.054 |
| | (0.160) | (0.140) | (0.159) |
| Voting rights | 0.194* | 0.235** | 0.244** |
| | (0.109) | (0.105) | (0.101) |
| Softcap use | −0.372*** | −0.389*** | −0.416*** |
| | (0.105) | (0.097) | (0.092) |
| Hardcap | −0.066** | −0.054* | −0.048* |
| | (0.031) | (0.032) | (0.029) |
| Telegram | −0.363** | −0.326*** | −0.443*** |
| | (0.139) | (0.110) | (0.125) |
| Listing | | | 0.398** |
| | | | (0.160) |
| Age | | | 0.083 |
| | | | (0.066) |
| Mean VIF | 1.77 | 1.70 | 1.75 |
| Maximum VIF | 3.07 | 3.05 | 3.20 |
| Year FE | Yes | Yes | Yes |
| Observations | 71 | 71 | 71 |
| Pseudo $R^2$ | 0.372 | 0.406 | 0.136 |
| Log pseudolikelihood | −32.210 | −30.438 | −26.275 |
| AIC | 94.421 | 90.876 | 88.551 |

*Note:* This table reports the robustness checks for the STO success determinants analysis. Models (1) to (3) are tobit estimations with a left-censoring at zero with the alternative success variable *Funding amount to target* as the dependent variable. The reference category for the countries is *Country other*. All models include a not reported constant. Heteroscedasticity-robust standard errors in parentheses. The symbols $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table 4.8.

In the alternative success specification, all signs remain unchanged, but the significance of *Pre-sale* disappears probably because of variation in our small sample (Lambert et al., 2022). The coefficient for *Transferability* is still positive and significant, confirming our prior results. Interestingly, the company-specific variable *Listing* now loads positive and significantly, which is consistent with our expectation that this is an effective signal of a firm's maturity. We can conclude that the robustness check does not show major deviations from the main analysis.

There is a potential endogeneity issue with the explanatory variables *Pre-sale* and *Transferability* and the dependent variable *Funding amount*. An STO-issuing company might choose these features while there are some unobserved characteristics, such as the quality of the STO or the issuing company, that may affect both the choice of a *Pre-Sale* or *Transferability* of the issuer and the funding success. As a matter of fact, investors do not necessarily base their investment decision on *Pre-sale* and *Transferability*, but on other unobserved features. Consequently, we cannot completely rule out the possibility that our results are subject to an omitted variable bias.

## 4.5 Post-STO phase

### 4.5.1 Overview of ST secondary markets

The secondary marketplaces where security tokens can be traded are either centralized exchanges (CEX) or decentralized exchanges (DEX). Decentralized exchanges are one application case in the decentralized finance ecosystem and are marketplaces where transactions are performed through self-executing smart contracts without an intermediary. The key technical innovation of most DEX is a new model for liquidity provision called automated market making (AMM). While on a CEX, market-making works with conventional limit order books and trades are settled on centralized servers *off-chain*, on a DEX it is automated *on-chain* via trading against a liquidity pool, a pool of tokens locked in a smart contract (Aoyagi, 2020).[5] Prices on a DEX are calculated automatically by an algorithm based on the liquidity that can be provided by anyone (Barbon and Ranaldo, 2022). Along with this, users of DEX retain control over the private key of their token instead of transferring it to the exchange platform, as in the case of CEX. Therefore, the tokens cannot be stolen during a hacker attack, ultimately lowering the counterparty risk (Lin, 2019). DEX can pave the way towards an 'on-ramping' of the tokens on a regulated CEX at a later point in time (Aspris et al., 2021). In the US, CEX need to be registered as Alternative Trading Systems (ATS); in Europe, they need an equivalent license as Multilateral Trading Facility

[5]For a detailed description of the functioning of AMM and liquidity pools see Barbon and Ranaldo (2022), Lehar and Parlour (2022), Mohan (2022), and Schär (2021).

(MTF), and they have to screen potential investors with respect to compliance to KYC and AML/CTF regulations.

The choice of the marketplace by the STO issuer can be a signal of the quality of the security token. CEX screen the potential tokens to be listed and typically charge high listing fees as high entry barriers, which only high-quality companies with good future prospects can afford. In addition, CEX function similarly to traditional online marketplaces where investors do not need to be familiar with blockchain technology, making it easier to reach any investor. In contrast, DEX are not regulated, there is no listing fee, but they require familiarity with blockchain technology. Therefore, we assume that trading on a CEX, as opposed to trading on a DEX, is a signal for high-quality tokens and companies.

### 4.5.2 Data of STO Underpricing

Our first source for secondary market data is *stomarket.com*, and from there, we move to various exchange platforms.[6] The second data source are the blockchain explorers *ethplorer.io* and *etherscan.io* for information on the ownership structure. A concern of our dataset from the success determinants analysis is that only a minority of these security tokens are later listed on secondary markets.[7] This has multiple causes since we argued previously that not all projects intend to trade the tokens, and other projects are not successfully funded. The phenomenon of sample reduction is also commonly known in the ICO context (Fisch and Momtaz, 2020; Lyandres et al., 2022). Benedetti and Kostovetsky (2021) state that the majority of the money invested in ICOs is in tokens later listed on secondary markets. We complement the secondary market data for a holistic picture of the market by real estate STOs (RE STOs). We acknowledge that there may be some comparability issues between conventional and RE STOs. As in equity markets, though, the underlying business model is not as crucial to returns, liquidity, and related research questions, as REITs in indexes demonstrate. The RE STOs in our sample are not directly tokenized real estate, as this is currently difficult to implement from a legal perspective. As such, a special purpose vehicle is tokenized with the property as the only asset, and investors hold a deed to the cash flows of the company rather than acquiring ownership rights to the property. Additionally, the primary offering of RE STOs cannot be analyzed in the same multivariate setting as 'conventional STOs' in Section 4.4. The value of a property, based on the *Funding amount*, is mainly determined by its property characteristics, such

[6]We consider the following CEX and DEX for security tokens in our analysis: tZERO, INX Securities, Tokensoft, Openfinance, CryptoSX, Securitize Markets, Uniswap, Levinswap, StellarX, and MERJ.

[7]Note that there is a difference between the *Transferability* analyzed in Section 4.4 and the listing on the secondary market. *Transferability* refers to the technical property that the programmer has allowed the tokens to be transferable after the issuance when programming the smart contract, which companies can disclose in the STO prospectus. Whether a company actually lists the tokens on the secondary market is an entirely different matter, for which *Transferability* is merely the technical prerequisite.

as size, location, or type of use. As such, information asymmetries during the primary offering and signals to overcome them differ strongly. In addition, the inclusion of the real estate sector seems reasonable, as Howell et al. (2020) document that the success of token offerings is particularly pronounced when it comes to business models that involve the tokenization of real assets. Nevertheless, when the tokens enter the secondary market, the market dynamics close these information asymmetries, and the market valuation, as well as the trading behavior, are similar. In any type of STO, investors receive regular cash flows from their tokens, whether in the form of a dividend, coupon, or rent payment. As mentioned earlier, this study focuses on the technical aspects of new funding mechanisms on the blockchain, which is why we consider RE STOs as valuable additional observations. Our sample covers the period from January 1st, 2019, to 31st December, 2021. The time difference of one year compared to the success determinants sample is due to the fact that many tokens are not immediately traded on secondary markets or are even legally ineligible because of lock-up periods, as in the US.

### 4.5.3 Variables STO Underpricing

Our dependent variable in the following analysis is *Underpricing*, which we define as the return in Equation 4.1 between the price of the token in the STO $P_{i,0}$ and the first traceable price on the market $P_{i,1}$.[8]

$$Underpricing = \frac{1}{n}\sum_{i=1}^{n}\frac{P_{i,1} - P_{i,0}}{P_{i,0}} \tag{4.1}$$

In the IPO literature, underpricing is a well-known phenomenon for which a plethora of theories, periods, and results in multiple markets have been investigated over the years.[9] In the following, we transfer explanatory approaches from IPOs that are relevant to the STO context. We also incorporate insights from technology and 'New market' IPOs, as they may have similarities to security tokens due to the technological component. First, we refer to the *market liquidity hypothesis* of Aggarwal et al. (2002), which suggests that companies pursuing a token offering face pressure to underprice to obtain market liquidity to signal their future growth potential. As a result, companies generate information momentum that attracts widespread interest from the media and analysts (Aggarwal et al., 2002), who may also perform certification functions of the issuer (Booth and Smith, 1986). This liquidity enables the companies to reduce illiquidity premia, compensates early investors for the undertaken risk, and causes network effects (Momtaz, 2020). Consequently, the

[8] Contrary to our approach, other studies in the ICO context refer to as underpricing the first-day-return between the opening and closing price on the first trading day (Momtaz, 2020, 2021a), which we calculate separately in Section 4.5.6.

[9] For a literature review on underpricing, see Ljungqvist (2007).

potential liquidity generated by underpricing is an opportunity for companies to attract investors (Brau and Fawcett, 2006), while it also serves to mitigate information asymmetries. Further, another related theory is that higher information asymmetries are associated with higher underpricing (Rock, 1986; Welch, 1989), based on Ritter (1984) who finds that high-risk IPOs are more underpriced, which provides an explanation for hot issue markets in periods with a large proportion of high-risk IPOs and high underpricing. This phenomenon can also apply to STOs since most companies undertaking an STO cannot present a comprehensive track record, experience, or a market-ready product resulting in high information asymmetries.

To analyze the influence of different investors involved in STOs as outlined in Hypothesis 3, we include the *No. large investors* as a numerical count of the number of investors who hold a share of more than 5% of all issued tokens. We use the 5% threshold related to the Schedule 13D filing, a disclosure requirement to the SEC in the US for investors who acquire more than 5% of the beneficial ownership of a company. We derive the ownership information from the blockchain explorers at the date of the token issuance.[10] To test Hypothesis 4, we consider the variable *Sentiment* as the 30-day return of Ether on the first day of trading. As stated in Section 4.2, Ethereum is the dominant blockchain platform for STOs, and therefore, the return of the corresponding native token Ether is an appropriate benchmark for the underlying market sentiment. We derive the data from *Coinmarketcap*.

We further control for the *Public float* of the tokens, which represents the percentage of the issued tokens that is attributed to investors who hold a share of less than 5%. A higher share of *Public float* was found to increase liquidity on stock markets (Ding et al., 2016). We include the logarithm of the *Trading volume* during the first 24 hours of trading. This measure reflects the actual interest of investors in an STO, resulting in a movement to the true market price (Felix and von Eije, 2019). For IPOs, Schultz and Zaman (1994) provide empirical evidence that underpriced stocks are traded more often on the first trading day than fully-priced stocks. We consider the dummy-variable *DEX*, which equals 1 if the token is traded on a decentralized exchange and 0 if it is traded on a centralized exchange. To take into account the prior success in the STO as analyzed in Section 4.4, we consider the logarithms of the variables *Funding amount* and *Token price*. Furthermore, we include the dummy-variable *STO type*, which equals 1 for 'conventional STOs' and 0 for real estate STOs to control for potential differences regarding *Underpricing*.

[10]We only consider unique wallet addresses of investors and their shares. However, due to blockchain technology, we cannot further ascertain what kind of investor it is.

### 4.5.4 Descriptive Statistics STO Underpricing

We present the descriptive statistics for the variables used in the STO underpricing analysis in Table 4.4.[11]

Table 4.4: Descriptive statistics for STO Underpricing.

| Statistic | N | Mean | SD | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Dependent variable:* | | | | | | | | |
| Underpricing | 106 | 0.012 | 0.144 | −0.156 | −0.054 | −0.021 | 0.007 | 0.490 |
| *Independent variables* | | | | | | | | |
| No. large investors | 106 | 3.132 | 1.574 | 1.000 | 2.000 | 3.000 | 4.000 | 10.000 |
| Sentiment | 107 | −0.001 | 0.236 | −0.583 | −0.113 | −0.113 | 0.098 | 1.289 |
| Public float | 106 | 0.404 | 0.322 | 0.000 | 0.050 | 0.526 | 0.705 | 0.862 |
| Trading volume | 107 | 3.187 | 2.477 | 0.000 | 1.800 | 2.700 | 4.200 | 12.000 |
| DEX | 106 | 0.830 | 0.377 | 0.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Funding amount | 106 | 12.238 | 2.590 | 0.000 | 11.031 | 11.110 | 12.932 | 18.713 |
| Token price | 106 | 3.481 | 1.296 | 0.010 | 3.891 | 3.961 | 4.009 | 7.311 |
| STO type | 107 | 0.196 | 0.410 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |

*Note:* This table reports the descriptive statistics (mean, standard deviation, minimum, 25$^{th}$ percentile, median, 75$^{th}$ percentile, and maximum) for the full sample. The variable *Underpricing* is winsorized at the top and bottom 5%. All variables are defined in Table 4.8.

We winsorize *Underpricing* at the top and bottom 5% to account for extreme outliers. The average *Underpricing* amounts to 1.2% with a median value of -2.1%. This means that the average STO leaves money on the table, whereas the median indicates overpricing at the cost of the investors. Both the mean and the median values are not far from zero, implying that the majority of the tokens are correctly priced. The minimum of -15.6% and maximum of 49.0% show that there are also companies with extreme over-and underpricing. In general, there does not appear to be underpricing in the ST market, as young companies lack experience, and the market is still in its infancy. The various results for *Underpricing* in 'New market' or tech IPOs and for ICOs are substantially higher (Adhami et al., 2018; Drobetz et al., 2019; Felix and von Eije, 2019; Giudici and Roosenboom, 2004; Kiss and Stehle, 2002). This may suggest that the 'New market' is not technologically comparable to blockchain and STOs, or the period under study is the cause of the discrepancies in the results. For ICOs, this is not surprising, as information asymmetries are much more pronounced in completely unregulated ICOs than in STOs. For STOs, the ventures have to issue regulation-compliant prospectus, while unaudited white papers in ICOs mainly present basic information (Florysiak and Schandlbauer, 2022).

[11] Additional detailed descriptive statistics for the conventional STO and RE STO sub-samples are presented separately in Table 4.10 in the Appendix. It can be observed that there is a disparity between the *Funding amount* and the *Token price* of conventional and RE STOs. However, since the dependent variable *Underpricing* is a fraction of prices, the absolute differences regarding higher *Funding amounts* or *Token prices* are thus scale-free.

In an average ST traded on secondary markets, 3.132 large investors are involved at the date of the issuance. The *Sentiment* shows that security tokens become listed on the secondary market on average during days of slightly negative or neutral sentiment represented with -0.1% of the 30-day Ether return, while the minimum of -58.4% and maximum of 128.9% demonstrate the great variation of crypto returns.[12] On average, a share of 40.4% of all security tokens is attributed to the *Public float*. The logarithm of the *Trading volume* during the first 24 hours of trading has a mean of 3.187 which represents $24.22. In our sample, 83.0% of the security tokens are traded on a *DEX* and the remaining on a regulated CEX. We use logarithms for the variables *Funding amount* for which the average is 12.238, corresponding to $206,489, and the *Token price* with 3.481, which corresponds to $32.49. The *STO type* reveals that 19.6% of the STOs are 'conventional STOs' and the remaining real estate STOs. Table 4.11 in the Appendix shows the correlation coefficients for all variables. Although there are occasional higher correlations between *DEX* and the *Funding amount* of -0.784 or the *Token Price* with -0.716, all other correlations are below 0.5. Therefore, we do not include these variables in the same model since they could bias the regression coefficients. We report the VIFs in Table 4.5, all of which are far below a conservative critical value of 5. Hence, multicollinearity is unlikely to be an issue in the subsequent analysis.

### 4.5.5 Multivariate Analysis: STO Underpricing

The regression estimations of the determinants of STO underpricing are reported in Table 4.5.

The signs of the coefficients are consistent across the model specifications, and the adjusted $R^2$ amounts to about 35% in all models. The coefficient of *No. large investors* is only in model (2) significant at the 10% level on *Underpricing*. It appears that the *increased monitoring hypothesis* does not apply to the STO context. A possible explanation for this could be that Stoughton and Zechner (1998) refer to IPOs and thus pure equity, although our sample also includes debt or funds with different pricing dynamics. Notably, this finding aligns with the counter-intuitive results of Franzke (2004), which suggest that VC-backed IPOs, to which increased monitoring activities are attributed, experience higher levels of underpricing in the German 'New market' compared to those without VC-backing. To summarize, we cannot provide statistical support in favor of Hypothesis 3. We find a positive significant link between *Sentiment* and *Underpricing*. A one-standard-deviation increase in *Sentiment* is in the model (1) associated with a 36.38% increase in *Underpricing* relative to the average. The results indicate that the *Sentiment* increases *Underpricing*, and issuers seem to time the first trading of their tokens to periods of positive market sentiment,

[12] Note that since the beginning of the observation period, the Ether price has increased from $141 in January 2019 to $3,683 in December 2021.

Table 4.5: Determinants of Underpricing.

| | *Dependent variable: Underpricing* | | | | | |
|---|---|---|---|---|---|---|
| | *OLS* | | | *Heckman* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| No. large investors | 0.015 | 0.015* | 0.011 | 0.014 | 0.012 | 0.010 |
| | (0.010) | (0.008) | (0.008) | (0.010) | (0.008) | (0.009) |
| Sentiment | 0.222*** | 0.227*** | 0.216*** | 0.241*** | 0.236*** | 0.218*** |
| | (0.064) | (0.062) | (0.064) | (0.057) | (0.058) | (0.064) |
| Public float | 0.002 | 0.010 | 0.019 | −0.059 | −0.034 | −0.039 |
| | (0.030) | (0.029) | (0.028) | (0.072) | (0.082) | (0.093) |
| Trading volume | 0.015* | 0.015* | 0.016** | 0.015* | 0.014* | 0.016** |
| | (0.009) | (0.009) | (0.008) | (0.008) | (0.008) | (0.007) |
| DEX | −0.082 | | | −0.077 | | |
| | (0.060) | | | (0.054) | | |
| STO type | | 0.087 | | | 0.087* | |
| | | (0.054) | | | (0.051) | |
| Token price | | | −0.037** | | | −0.033** |
| | | | (0.015) | | | (0.016) |
| Mean VIF | 1.142 | 1.136 | 1.095 | | | |
| Maximum VIF | 1.230 | 1.194 | 1.110 | | | |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 105 | 105 | 105 | 254 | 254 | 254 |
| Adjusted $R^2$ | 0.343 | 0.351 | 0.405 | | | |
| Log Likelihood | | | | −48.053 | −47.319 | −45.062 |
| $\rho$ | | | | −0.426 | −0.343 | −0.385 |

*Note:* This table reports cross-sectional OLS regressions for the determinants of STO Underpricing in models (1) to (3). Models (4) to (6) present the results from the Heckman (1979) procedure using maximum likelihood estimation with the selection variable *Funding amount*. Heteroscedasticity-robust standard errors in parentheses. All models include a not reported constant. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Table 4.8.

which serves as a positive external signal. Our findings are in line with the IPO (Ljungqvist et al., 2006) as well as the ICO (Felix and von Eije, 2019) literature. Thus the conjecture in Hypothesis 4 that the crypto market *Sentiment* has a positive influence on *Underpricing* is supported by our empirical evidence. As for our control variables, the coefficient of *Trading volume* is across all model specifications positive on *Underpricing*. The results align with IPO (Zheng and Li, 2008) and ICO literature (Felix and von Eije, 2019). None of our model specifications yield a significant effect of *DEX* and *STO type*, which is why we cannot observe any significant difference between tokens traded on centralized and decentralized exchanges or 'conventional' and RE STOs regarding *Underpricing*.[13]

[13]We would like to point out that the signs and significances are consistent across all model specifications, regardless of whether the *Funding amount* and *Token price* are included, or not.

A major criticism could be that this sample potentially suffers from a selection bias resulting from issuers that offer the tokens with a larger discount during the initial offering in order to increase the chance of a subsequent listing. We address this issue similarly to Benedetti and Kostovetsky (2021) and Florysiak and Schandlbauer (2022) by applying the Heckman selection model (Heckman, 1976, 1979). We perform a full information maximum likelihood estimation with the selection variable *Funding amount* since this is the major variable of STO success (as outlined in Section 4.4) and crucial for a token to become listed. We can therefore address this sample selection problem in a methodologically appropriate way and consider all listed and unlisted STOs simultaneously, which increases the number of observations. The descriptive statistics for this sample are displayed in Table 4.10 in Panel C in the Appendix. Models (4) to (6) in Table 4.5 display the results from the Heckman procedure and have consistent signs as the previous models. We observe that *No. large investors* is no longer significant, whereas the positive and significant influence of *Sentiment* on *Underpricing* remains. Interestingly, in the model (5), the *STO type* is significant on the 10% level on *Underpricing*, meaning that 'conventional STOs' have a higher *Underpricing* in comparison to real estate STOs. This could be due to the fact that the price of real estate can be more accurately determined and is more transparent to the public, making these STOs more likely to be priced correctly. We conclude that a potential selection bias is rather unlikely to be driving our results.

### 4.5.6 Returns to investors after the token listing

As a further market valuation, we validate the previously sent signals about the quality of the STO by examining secondary market returns. We analyze buy-and-hold returns (BHR) as well as buy-and-hold-abnormal returns (BHAR) of investors who buy the security tokens on the first day the token is traded on an exchange and hold the token for different short-term time horizons ranging from one day to one year. We concentrate on this approach since, e.g. the common risk factor models of Fama and French (1993) and Carhart (1997) rely on a longer data history to calculate expected returns, which is not yet available for security tokens. We calculate the raw buy-and-hold return ($BHR$) in the same way as *Underpricing*, but from the first day of trading $t = 1$ to the last day of the holding period $T$.

$$BHR = \frac{1}{n} \sum_{i=1}^{n} \frac{P_{i,T} - P_{i,t=1}}{P_{i,t=1}} \tag{4.2}$$

Alternatively, to calculate the buy-and-hold abnormal return ($BHAR$), we adjust the raw return by a value-weighted market capitalization-based benchmark, similar to Fisch and

Momtaz (2020) and Momtaz (2021a) as follows:

$$BHAR = \frac{1}{n}\sum_{i=1}^{m}\Big[\frac{P_{i,t=T} - P_{i,t=1}}{P_{i,t=1}} - \sum_{j=1,j\neq i}^{n}\frac{MC_{j,t=T}}{\sum_{j=1}^{n} MC_{j,t=T}} \cdot \frac{P_{j,t=T} - P_{j,t=1}}{P_{j,t=1}}\Big], \quad (4.3)$$

where $P_{i,t=1}$ is the price of the security token $i$ at the end of the holding period $T$ and $MC_{j,t}$ refers to the market capitalization of the security token $j$ on day $T$ ($i{\neq}j$). The market consists of all security tokens with available price data. The value-weighted market benchmark is the product of the raw return of every other security token $j$ over the holding period $T$ and the market capitalization of a security token $j$ over the sum of the whole market capitalization at the end of the holding period $T$. The adjustment for the market capitalization is suitable for several reasons. Firstly, some small-cap firms experience extreme returns, which could cause severe distortions of the results when using, e.g. volume-weighted or equally-weighted benchmarks (Momtaz, 2020). Secondly, market capitalization is subject to boom-and-bust cycles in the entire token market (Chen et al., 2021), which we can take into account in this way. The results of the *BHR* and *BHAR* analysis are displayed in Table 4.6.

Table 4.6: Analysis of BHR and BHAR.

| | | *BHR* Mean (Median) | *BHAR* Mean (Median) | Volatility |
|---|---|---|---|---|
| 1 Day | 106 | 0.231 | 0.229 | 0.258 |
| | | (0.010*) | (0.002) | |
| 1 Week | 106 | 0.015 | −0.105** | 0.364 |
| | | (−0.030**) | (−0.088**) | |
| 1 Month | 105 | 0.037 | −0.152** | 0.318 |
| | | (−0.019*) | (−0.026*) | |
| 2 Months | 102 | 0.062* | −0.300 | 0.330 |
| | | (0.006*) | (0.020) | |
| 3 Months | 98 | 0.050 | −0.364 | 0.324 |
| | | (0.006**) | (−0.077**) | |
| 6 Months | 87 | 0.092* | −0.342** | 0.420 |
| | | (−0.005) | (−0.351**) | |
| 1 Year | 24 | 0.549 | 0.136 | 2.256 |
| | | (−0.011) | (0.047) | |

*Note:* This table reports the raw buy-and-hold returns (BHR) and buy-and-hold abnormal returns (BHAR) adjusted by a value-weighted market capitalization-based benchmark over different short-time horizons ranging from one day to one year. The mean, in parentheses, the median, and the volatility are displayed. The symbols * and ** denote significance at the 5% and 1% levels, respectively. All variables are defined in Table 4.8.

Both the *BHRs* and *BHARs* vary depending on the investment horizon. The number of tokens diminishes over time, as many tokens have been listed in the last year of the observation period, and others have no continuous trading history as they, e.g., changed the exchange platform to increase liquidity. Similar to the results in the ICO literature, we document partly extreme high ratios of mean to the median that exemplify the highly skewed distribution of returns in the market for tokens (Momtaz, 2021a). Particularly the high negative mean $BHARs$ for holding periods between one week of -10.5% to six months of -34.2% trace back to the current situation on ST secondary markets where a few tokens which suffered substantial decreases in value make up the majority of the market capitalization. On the one hand, this shows the high probability of losses and, on the other, provides further evidence for the rationale that investors need to be compensated for the high risk they take by investing in a company with a weak track record (Benedetti and Kostovetsky, 2021). These findings are consistent with Kiss and Stehle (2002), who observe a post-IPO underperformance in the 'New market' between 1997 and 2001. A naïve investor who invests the same amount of money in every security token experienced, e.g., for a holding period of six months, a positive $BHR$ of 9.2%, indicating potential wealth gains. Nevertheless, the corresponding medians fluctuate around the zero point over any holding period. In contrast, considering market capitalization, a security token investor realizes partially extreme negative and positive mean values of the $BHAR$. The medians draw a similar picture. To conclude this section of the post-STO performance, we observe both extremely negative and positive $BHR$ and $BHAR$ over different short-term investment horizons.

### 4.5.7 (Il-)liquidity on secondary ST markets

A key benefit and promise of digital tokens is liquidity due to reduced costs and faster settlement times on the blockchain (Yermack, 2017), particularly because of the new method of liquidity provision on DEX. We investigate the liquidity situation on the ST secondary market since its inception, as liquidity is central for future industry development. In Figure 4.1, we display the development over time of several key characteristics of ST secondary markets.

The *Market capitalization* shows a strong positive trend, with stagnation in 2019 and during the beginning of the Covid-19 pandemic, followed by a strong growth trend. A similarly positive growth trend is evident for the daily *Trading volume*. The high variability of the daily *Trading volume* relies on the fact that CEXs partly have trading hours just like conventional trading platforms and DEX operate continuously.

The liquidity situation on the market can be explained by the 'chicken-and-egg' problem, at least in the beginning when mainly CEX operated. On the one hand, investors expect

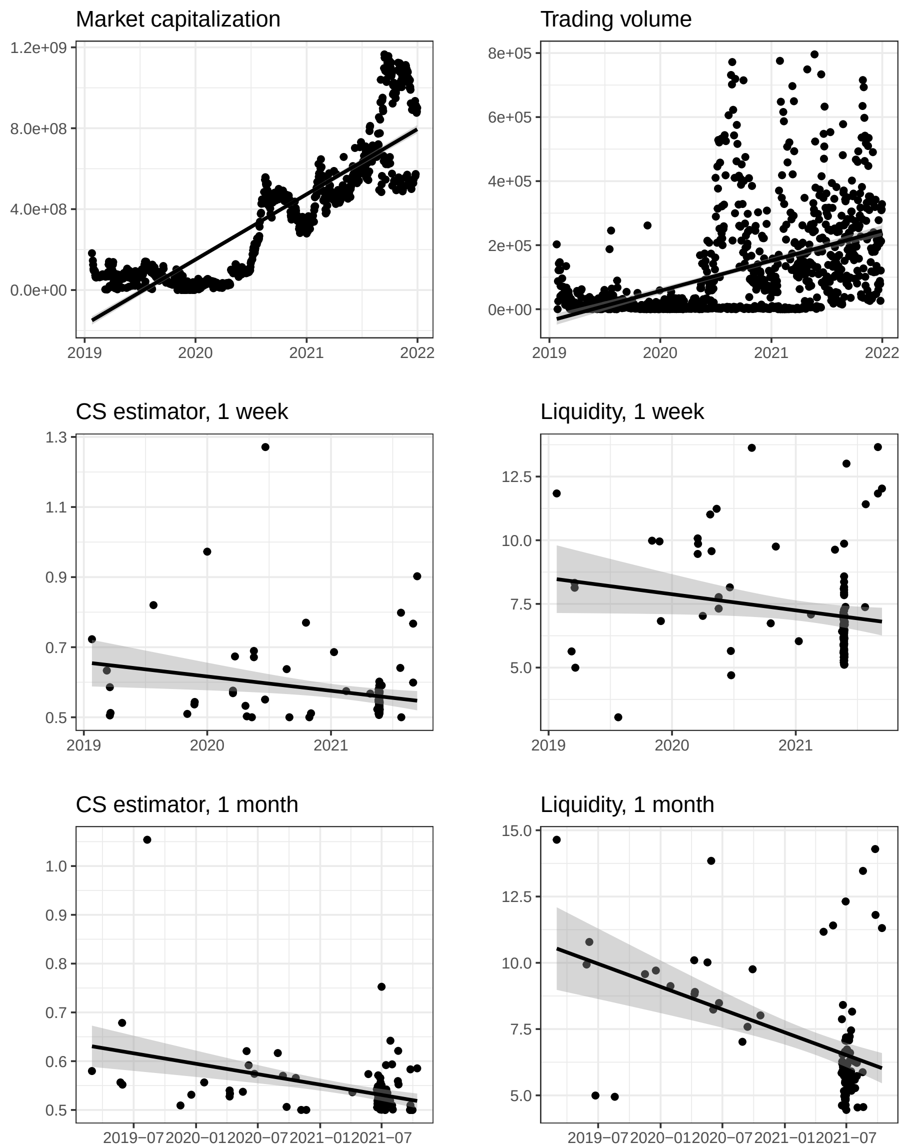



Figure 4.1: This Figure presents the evolution of the security token secondary market from 1st January 2019 until 31st December 2021. The black line is the best-fit line. The *Trading volume* is censored at $800,000 because of the scaling. The variables are defined in Table 4.8. N=108.

to trade many different qualitative tokens while issuers will only pay the listing fees of the exchanges if the latter provides liquidity (Lambert et al., 2022). The analysis of the liquidity in cryptocurrency markets faces the problem of lacking high-frequency intraday data to determine high-frequency bid-ask spreads (Brauneis et al., 2021). As such, other metrics addressing the issue of low-frequency liquidity markets have to be considered. Firstly, we calculate the *CS estimator* of Corwin and Schultz (2012) as a simple bid-ask spread from daily high and low prices; see the detailed formula in the Appendix. Secondly, we compute *Liquidity* based on a modified version of the illiquidity measure of Amihud (2002) and Amihud et al. (2006), which originally determines the trading volume required to move the price by 1%, as follows:

$$Liquidity_t = -log\frac{1}{5}\left[\sum_{t=t-5}^{t}\frac{|log(\frac{p_t}{p_{t-1}})|}{p_t \cdot volume_t}\right], \tag{4.4}$$

where it is multiplied by the negative of the logarithm to facilitate the numerical interpretation (Howell et al., 2018; Lyandres et al., 2019).[14] We consider both measures over an observation period of one week and one month after the first trading day and average them over five days. Figure 4.1 reveals that a large number of tokens were newly listed in 2021, which are mainly tokens on DEXs, as DeFi experienced tremendous growth in 2021.[15] The decrease of the *CS estimator* in Figure 4.1 over time indicates that the spread diminished, which is indicative of a more liquid market. Contrary, our *Liquidity* measure decreased over time, suggesting that especially newly issued tokens are less liquid. Brauneis et al. (2021) point out that, when studying liquidity levels, the Amihud et al. (2006) measure taking into account the *Trading volume* outperforms and is more meaningful than the *CS estimator*. Therefore, we conclude a general decreasing trend in liquidity on security token secondary markets over time. The graphical findings are empirically extended in the following. The calculation of our metrics with a sample split in CEX and DEX with a corresponding Welch $t$-Test for differences in mean (Welch, 1947) and the Mood Median-Test for differences in the median (Mood, 1950) are reported in Table 4.7.

The mean (median) *CS estimator* after a trading period of one week amounts for a CEX to 0.64 (0.59) and for a DEX 0.56 (0.54), whereas after one month, it is 0.58 (0.54) and 0.53 (0.52). A direct comparison of centralized and decentralized exchanges is not possible as the differences in mean and median are not significant. The mean (median) values of the *Liquidity* measure for a trading period of one week is on a CEX with 9.27 (9.66) and substantially lower for a DEX with 6.76 (6.45). The differences in mean and median are statistically significant, which underpins that decentralized exchanges are less liquid than centralized ones. For a trading period of one month, this finding is confirmed in the same way with an average (median) *Liquidity* on a CEX with 10.82 (9.66) and on a DEX with 6.67 (6.45) and highly significant differences in mean and median. These results are in line with Aspris et al. (2021), who find that CEXs are more liquid and that these tokens have a higher market capitalization which implies market segmentation and a reduction of governance risk. Hasbrouck et al. (2022) propose an increase in trading fees in an economic model as a solution to the low trading volumes on DEX. Both the *CS estimator* and the *Liquidity* measure reflect an increase in liquidity for prolonging the trading period from one week to one month. This fact is not surprising as trading activity can be limited in

[14]The liquidity analysis is only included in the working paper version in Howell et al. (2018).

[15]We account for the increase of observations in 2021 in the empirical analysis with year-fixed effects in the underpricing regression models in Table 4.5, and we additionally verified the results in unreported analysis with a sample split and found no changes in our results.

Table 4.7: Security Token market characteristics.

| | | Exchange type | | Tests | |
|---|---|---|---|---|---|
| | | CEX | DEX | Mean Diff. | Median Diff. |
| **CS estimator, 1 week** | Mean | 0.64 | 0.56 | $t = 2.14$** | |
| | Median | 0.59 | 0.54 | | $X^2 = 0.67$ |
| | SD | 0.15 | 0.09 | | |
| **CS estimator, 1 month** | Mean | 0.58 | 0.53 | $t = 1.47$ | |
| | Median | 0.54 | 0.52 | | $X^2 = 1.12$ |
| | SD | 0.13 | 0.04 | | |
| **Liquidity, 1 week** | Mean | 9.27 | 6.76 | $t = 2.93$*** | |
| | Median | 9.66 | 6.45 | | $X^2 = 3.62$* |
| | SD | 3.39 | 1.33 | | |
| **Liquidity, 1 month** | Mean | 10.82 | 6.31 | $t = 5.36$*** | |
| | Median | 11.24 | 5.92 | | $X^2 = 6.73$*** |
| | SD | 3.09 | 1.45 | | |
| | N | 18 | 89 | | |

*Note:* This table reports the mean, median, and SD (standard deviation) for the *CS estimator* and *Liquidity* after a trading period of one week and one month averaged over the last five days. The sample is split into centralized exchanges (CEX) and decentralized exchanges (DEX), for which the corresponding differences in mean are tested with a Welch *t*-Test and differences in the median with a Mood Median Test. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Table 4.8.

the first trading days because the exact start of trading is not communicated beforehand, and investors on a CEX have to transfer their tokens to the platforms first before they start trading (Chanson et al., 2018). As comparative values to our results in terms of *Liquidity*, we consider utility tokens from ICOs with a mean value of 12.59 and NASDAQ shares as an industry benchmark with a much higher value of 18.16 (Howell et al., 2018). This comparison reveals that the security tokens in our sample are less liquid than other investment possibilities.

Overall, it may seem as if liquidity has deteriorated over time, and the situation on security token secondary markets has worsened. However, more tokens have been listed primarily on less liquid DEXs over time. This is an indication of the slow completion of the range and the maturation of the market, which is driven by the increasing adoption of DEXs. For the tokens with low liquidity, it would have otherwise been unlikely to become listed on the secondary market at all. In this case, DEXs offer a simple way for a listing with low entry barriers and perspectives for a (cross-)listing on a CEX in the future, which so far is mainly used by high-quality security tokens. Meanwhile, the main problem is no longer the infrastructure but the lack of liquidity, which manifests itself in technology and global regulatory uncertainty as well as security concerns – in sum: trust and confidence in the system.

## 4.6 Conclusion

Security token offerings are a means for companies to raise capital where they issue digital tokens as regulated investment products on the blockchain. In this paper, we examine how signaling affects the market participants in the primary and secondary markets for security tokens, such as the STO-issuing company or investors in the primary and secondary markets. In order to obtain a holistic picture of the signaling effect on the entire market, we analyze market outcomes in the pre-STO phase and in the post-STO phase. We study success determinants of STOs which are a way for issuers to signal their quality to investors to overcome information asymmetries during the primary offering in the pre-STO phase. We find that both the execution of a pre-sale phase as a method to gather price-relevant information prior to the main funding and the announcement of token transferability as the expectation of future liquidity are positively linked to the funding success. In the post-STO phase, we find evidence that security tokens are almost correctly priced with a mean (median) of 1.2% (-2.1%), indicating that issuers do not use underpricing as a way to attract investors. Drawing on the literature on IPOs, we show that underpricing is positively related to the sentiment on the crypto market, which serves as a positive external signal, and companies time the first notation of their tokens to avoid phases of negative market sentiment. Finally, the market valuation should reveal the true quality of security tokens. We find that over various short time horizons, both extremely positive and negative buy-and-hold (abnormal) returns can be achieved by an investor. Moreover, we conclude that the security token market lacks professionalism in investment evaluation and selection, as a naïve diversification strategy is a more promising approach to achieving higher returns. We find that liquidity after the start of trading has decreased since the inception of the secondary market. However, this finding relies on the increasing number of tokens on less liquid decentralized exchanges. These exchanges offer lower entry barriers and complete the supply on the secondary market.

Our results highlight that companies that intend to raise funding via STOs would be well advised to offer a pre-sale phase in their STO and assure their intentions to trade the tokens on the secondary market while already devising a plan for successful future trading. From an investor's perspective, these signals can be interpreted as positive quality signals on the basis of which appropriate investment decisions are conducted. Nonetheless, since extremely negative returns can also be achieved in the short term and there seems to be a lack of liquidity in the secondary market, investors should be well versed in the technical fundamentals and risks of blockchain investments. At this point, the legislator could also exert influence without at the same time over-regulating and hindering the further growth of the industry.

Our study has limitations. Because of the exclusion of several STOs due to limited data availability and the hand-collection of the data, we cannot completely rule out the possibility that a potential selection bias is present in our data. Therefore, the generalization and external validity of our results is reduced. Nevertheless, we collected and cross-checked data from various sources, such as the companies' websites, LinkedIn-Pages, aggregator websites, white papers, regulated prospectus, blockchain explorers, as well as Telegram channels. Consequently, one avenue for future research is to generalize our findings in a larger sample within a more mature market with a greater variety of determinants, particularly more balanced between conventional and RE STOs for the analysis of underpricing. Besides, we can only consider the returns to investors resulting from the changes in the token's value and cannot observe and include interest and dividend payments.

Most STOs use the Ethereum blockchain, which merged to the proof-of-stake consensus mechanism in September 2022, silencing criticism of high energy consumption and setting the stage for greater scalability. Hence, this progression will contribute to the future development of the security token industry on a technological and cost level. In many jurisdictions, the record must still be paper-based or stored in a central governmental database (Lambert et al., 2022). It is necessary for regulators to enact legislation simplifying these processes. Since blockchain technology does not stop at national borders, legislation should ideally be implemented on a large scale, thus ensuring legal certainty for investors.

# Appendix

See Tables 4.8, 4.9, 4.10.

Table 4.8: Definition of all variables.

| Variable | Description | Source |
|---|---|---|
| **Pre-STO phase** | | |
| *Funding amount* | Logarithm of the amount of the achieved financing volume in USD | STO research |
| *Funding amount to target* | Percentage ratio of the amount of the achieved financing volume to the funding target (Hardcap) | STO research |
| *Transferability* | The variable indicates whether a company announces prior the STO that the issued security token will be transferable by the investor (=1), 0 otherwise. | STO research |
| *Equity token* | The variable indicates whether the token represents a share in equity (=1), 0 otherwise. | STO research |
| *Fund token* | The variable indicates whether the token represents a share in an investment fund (=1), 0 otherwise. | STO research |
| *Voting rights* | The variable indicates whether a voting right for the investor is securitized in the token (=1), 0 otherwise. | STO research |
| *Softcap use* | The variable indicates whether a funding threshold must be achieved to be completed (=1), 0 otherwise. | STO research |
| *Hardcap* | Logarithm of the pre-defined funding target in USD | STO research |
| *Telegram* | The variable indicates whether a company uses Telegram as a communication medium with potential investors as part of its STO (=1), 0 otherwise. | Telegram |
| *Listing* | The variable indicates whether the company is listed on a traditional stock exchange (=1), 0 otherwise. | STO research |
| *Age* | Logarithm of the difference from the start date of the STO and the date of foundation of the company | Own calculations |
| *Cayman Islands* | The variable indicates whether the company has been incorporated in the Cayman Islands (= 1), 0 otherwise. | STO research |
| *Europe* | The variable indicates whether the company has been incorporated in Europe (= 1), 0 otherwise. | STO research |
| *UK* | The variable indicates whether the company has been incorporated in the UK (= 1), 0 otherwise. | STO research |
| *USA* | The variable indicates whether the company has been incorporated in the USA (= 1), 0 otherwise. | STO research |
| **Post-STO Phase** | | |
| *Underpricing* | Raw return between token price in the STO and first price on the secondary market | Own calculations |
| *No. large investors* | Absolute numbers of investors with a share of more than 5% of all tokens at token issuance | Ethplorer, Etherscan |
| *Sentiment* | 30-day return of Ether (ETH) on the first trading day | Coinmarketcap |
| *Public float* | Percentage share of public float at token issuance | Ethplorer, Etherscan |
| *Trading volume* | Logarithm of the trading volume during the first 24 hours on an exchange platform in USD | Exchange Platforms |
| *DEX* | Dummy-variable which equals 1 for a decentralized exchange, 0 for a centralized exchange. | STO research |
| *Funding amount* | Logarithm of the funding amount in USD | STO research |

Continued on Next Page

| **Variable** | **Description** | **Source** |
|---|---|---|
| *Token price* | Logarithm of the token price during the STO in USD | STO research |
| *STO type* | Dummy-variable which equals 1 for a 'conventional' STO, 0 for a real estate STO (RE STO). | STO research |
| *Sec notation* | Dummy-variable which equals 1 for an STO listed on a CEX or DEX, 0 otherwise. | STO research |
| *BHR* | Raw buy-and-hold return | Own calculations |
| *BHAR* | Buy-and-hold abnormal return adjusted by a value-weighted market capitalization based benchmark | Own calculations |
| *CS estimator, 1 week* | Corwin and Schultz (2012) estimator one week after the start of trading averaged over the last five days | Own calculations |
| *CS estimator, 1 month* | Corwin and Schultz (2012) estimator one month after the start of trading averaged over the last five days | Own calculations |
| *Liquidity, 1 week* | Liquidity measure based on Amihud (2002) and Amihud et al. (2006) illiquidity, one week after the start of trading and averaged over the last five days | Own calculations |
| *Liquidity, 1 month* | Liquidity measure based on Amihud (2002) and Amihud et al. (2006) illiquidity, one month after the start of trading and averaged over the last five days | Own calculations |
| | | End of table |

*Note:* List and definitions of all variables with the corresponding source. The source 'STO research' comprises the comprehensive data collection process for the pre-STO phase on Digital Asset Network and various aggregator websites, company websites, EDGAR database, LinkedIn profiles, (legal) prospectus and white papers, blockchain explorers with the corresponding cross-check and for the post-STO phase the exchange platforms.

Table 4.9: Correlation matrix for STO success determinants.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Funding amount | 1 | | | | | | | | | | | |
| (2) Funding amount to target | 0.548 | 1 | | | | | | | | | | |
| (3) Pre−sale | 0.087 | −0.171 | 1 | | | | | | | | | |
| (4) Transferability | 0.196 | 0.143 | 0.031 | 1 | | | | | | | | |
| (5) Equity token | −0.001 | 0.048 | −0.092 | −0.047 | 1 | | | | | | | |
| (6) Fund token | 0.122 | −0.118 | 0.099 | 0.161 | −0.178 | 1 | | | | | | |
| (7) Voting rights | 0.136 | 0.135 | 0.094 | −0.078 | 0.169 | −0.169 | 1 | | | | | |
| (8) Softcap use | −0.394 | −0.410 | 0.111 | 0.075 | −0.013 | −0.028 | 0.030 | 1 | | | | |
| (9) Hardcap | −0.029 | −0.317 | 0.362 | 0.064 | −0.165 | 0.287 | −0.048 | 0.109 | 1 | | | |
| (10) Telegram | −0.149 | −0.268 | 0.492 | 0.285 | −0.038 | 0.224 | −0.024 | 0.151 | 0.356 | 1 | | |
| (11) Listing | −0.018 | 0.070 | 0.068 | −0.216 | 0.068 | −0.087 | −0.116 | 0.045 | −0.123 | −0.031 | 1 | |
| (12) Age | 0.100 | 0.181 | −0.064 | −0.053 | 0.069 | −0.063 | 0.108 | 0.005 | −0.221 | −0.136 | 0.194 | 1 |

*Note:* This table reports the Bravais-Pearson correlation coefficients for the STO success determinants analysis for the full sample. All variables are defined in Table 4.8.

Table 4.10: Detailed Descriptives for STO Underpricing.

| | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Conventional STOs** | | | | | | | | |
| Underpricing | 20 | 0.025 | 0.207 | -0.156 | -0.135 | 0.000 | 0.020 | 0.490 |
| No. large investors | 20 | 2.200 | 1.436 | 1.000 | 1.000 | 2.000 | 3.000 | 6.000 |
| Sentiment | 21 | 0.047 | 0.275 | -0.583 | -0.095 | 0.105 | 0.218 | 0.473 |
| Funding amount | 20 | 14.843 | 4.481 | 0.000 | 13.773 | 16.321 | 17.561 | 18.713 |
| Token price | 20 | 1.862 | 1.877 | 0.010 | 0.693 | 0.693 | 2.635 | 7.311 |
| Trading volume | 21 | 4.334 | 4.026 | 0.000 | 0.000 | 4.997 | 7.315 | 12.219 |
| Public float | 20 | 0.248 | 0.266 | 0.000 | 0.001 | 0.150 | 0.455 | 0.744 |
| DEX | 21 | 0.238 | 0.436 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 |
| **Panel B: Real Estate STOs** | | | | | | | | |
| Underpricing | 86 | 0.009 | 0.126 | -0.156 | -0.046 | -0.022 | 0.005 | 0.490 |
| No. large investors | 86 | 3.349 | 1.532 | 1.000 | 2.000 | 3.000 | 4.000 | 10.000 |
| Sentiment | 86 | -0.012 | 0.225 | -0.583 | -0.113 | -0.113 | 0.033 | 1.289 |
| Funding amount | 86 | 11.632 | 1.352 | 10.856 | 11.021 | 11.090 | 11.293 | 18.421 |
| Token price | 86 | 3.858 | 0.726 | 0.693 | 3.941 | 3.972 | 4.010 | 5.093 |
| Trading volume | 86 | 2.907 | 1.853 | 0.000 | 1.792 | 2.596 | 3.886 | 10.853 |
| Public float | 86 | 0.441 | 0.325 | 0.012 | 0.058 | 0.629 | 0.721 | 0.862 |
| DEX | 86 | 0.965 | 0.185 | 0.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| **Panel C: Sample Heckman selection model** | | | | | | | | |
| Sec notation | 254 | 0.416 | 0.494 | 0.000 | 0.000 | 0.000 | 1.000 | 1.000 |
| Funding amount | 254 | 11.596 | 3.600 | 0.000 | 10.995 | 11.220 | 13.221 | 18.713 |

*Note:* This table reports the descriptive statistics (number of observations, mean, standard deviation, minimum, $25^{th}$ percentile, median, $75^{th}$ percentile, and maximum) for conventional STOs (Panel A), Real Estate STOs (Panel B), and the selection equation of the sample for the Heckman selection model for listed and unlisted STOs (Panel C). All variables are defined in Table 4.8 in the Appendix.

Table 4.11: Correlation matrix for STO Underpricing.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) Underpricing | 1 | | | | | | | |
| (2) No. large investors | 0.280 | 1 | | | | | | |
| (3) Sentiment | 0.419 | 0.216 | 1 | | | | | |
| (4) Public float | −0.079 | 0.150 | 0.002 | 1 | | | | |
| (5) Trading volume | 0.375 | −0.046 | 0.195 | −0.140 | 1 | | | |
| (6) DEX | −0.187 | 0.168 | −0.204 | 0.250 | −0.303 | 1 | | |
| (7) Funding amount | 0.368 | −0.157 | 0.234 | −0.279 | 0.325 | −0.784 | 1 | |
| (8) Token price | −0.372 | −0.036 | −0.184 | 0.243 | −0.157 | 0.716 | −0.676 | 1 |

*Note:* This table reports the Bravais-Pearson correlation coefficients for STO Underpricing for the full sample. All variables are defined in Table 4.8.

### Calculation of the CS estimator

Calculation of the Corwin and Schultz (2012) estimator based on daily high ($H_t$) and low ($L_t$) prices of two consecutive time intervals $t$ and $t+1$

$$CS_{t,t+1} = \frac{2(exp(\alpha) - 1)}{1 + exp(\alpha)}$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}}$$

$$\beta = \left[ln\left(\frac{H_t}{L_t}\right)\right]^2 + \left[ln\left(\frac{H_{t+1}}{L_{t+1}}\right)\right]^2$$

$$\gamma = \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2$$

## Statements and Declarations

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The authors have no relevant financial or non-financial interests to disclose.

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There is no concern with ethical standards for this manuscript.

### Research Data Policy and Data Availability Statements

The data that support the findings of this study are available from the corresponding author upon request.

# Chapter 5

# Revealing the Risk Perception of Investors using Machine Learning

This chapter is based on a joint work with Marina Koelbl (University of Regensburg), Bertram I. Steininger (KTH Royal Institute of Technology, Stockholm), and Wolfgang Schaefers (University of Regensburg), and has been accepted for publication and is forthcoming in the *European Journal of Finance*.[1]

**Abstract**:Corporate disclosures convey crucial information to financial market participants. While machine learning algorithms are commonly used to extract this information, they often overlook the use of idiosyncratic terminology and industry-specific vocabulary within documents. This study uses an unsupervised machine learning algorithm, the Structural Topic Model, to overcome these issues. Our findings illustrate the link between machine-extracted risk factors discussed in corporate disclosures (10-Ks) and the corresponding pricing behavior by investors, focusing on a previously unexplored US REIT sample from 2005 to 2019. Surprisingly, when disclosed, most risk factors counterintuitively lead to a decrease in return volatility. This resolution of uncertainties surrounding known risk factors or the provision of additional facts about these factors contributes valuable insights to the financial market.

**Keywords** Risk, Textual Analysis, Machine Learning, Structural Topic Model, 10-K filing

[1] This paper circulated previously under the title: "Can Risks be Good News? Revealing Risk Perception of Real Estate Investors using Machine Learning".

## 5.1 Introduction

It is still a matter of academic debate, whether markets efficiently incorporate information into prices. In financial markets, pricing is a continuous process of investors' reactions to new information (Fama, 1970) characterized by its volatility around the expected value. A low volatility is a sign of consistent expectations across investors regarding values when new information emerges. Contrary, high volatility indicates dissent about how to value and incorporate new information. By revealing a piece of new information, a new pricing process begins after their release date resulting in three possible outcomes: no price reaction if the information is irrelevant or already known among the investors, increasing volatility if the investors are in disagreement with the pricing outcome of the information, or decreasing volatility if the investors coincide about the informational impact on the firm's future prospect. From a theoretical perspective, new information can increase or decrease investors' risk perception. In line with this ambiguity, empirical research identifies information factors increasing as well as decreasing the volatility; whereas the latter finding is in the majority. We use a machine-learning based approach to identify which information factors are positive or negative linked with risk to dissolve these mixed empirical findings.

Previous studies about market efficiency show theoretically and empirically that information asymmetry reduces market efficiency and increases stock misvaluation (e.g., Ross, 1973; Myers, 1984; Myers and Majluf, 1984; Miller and Rock, 1985). An effective tool to overcome this asymmetry is to inform the public of any relevant news helping them to make the right decision and thereby finding the right price. For the US, the Securities and Exchange Commission (SEC) demands various standardized disclosures of publicly listed firms to establish and maintain efficient markets. For that, firms are mandated to discuss the factors which make a firm speculative or risky in their 10-Ks (see Securities and Exchange Commission, 2005). Although all types of risk – whether quantified or described qualitatively – influence the decisions of managers and investors alike, mandatory risk disclosures in qualitative form (i.e. Item 1A – a section describing risk factors in 10-K filings) are less explored than in quantitative form (e.g., stock volatility).

Recognizing the temporal and cognitive limitation of humans to read and process to the massive amount of text, 'topic models' have gained great importance over the last few years both in industry and research. Topic models are statistical models used in natural language processing (NLP) and unsupervised machine learning (ML) to discover latent topics within documents. Their goal is to find the 'topics' embedded in textual data without any prior knowledge of the topics. These models are particularly useful for analyzing large sets of unstructured text data such as corporate disclosures. The Latent Dirichlet Allocation (LDA) method has become predominant in economics, accounting, and finance. The advantage of LDA is that it does not require predefined rules (i.e. a priori determined keywords aka bag of words) to quantify latent topics within; the disadvantage is that LDA tends to identify already known or trivial topics since the Dirichlet distribution assumes almost uncorrelated topics and ignores the existence of idiosyncratic language (covariate words) within a subset of the documents. Previous research (e.g., Lopez-Lira, 2020) shows this disadvantage wherein extracted topics closely align with the industrial sectors of the firms, as their textual content utilizes similar words. Consequently, LDA frequently reaffirms the existing classification, providing minimal new insights into why firms are exposed to specific risk topics. This methodical drawback is partly solved with its technical successor, the Correlated Topic Model (CTM, see Blei and Lafferty, 2007) which has so far not been used empirically. Even if sophisticated approaches have been developed over the last years (e.g., Cong et al., 2019; Kelly et al., 2021; Li et al., 2021; Das et al., 2022), they are not widely used in the accounting and financial domain.

To overcome the problems encountered in the quantitative analysis of textual disclosures, we propose the application of the Structural Topic Model (STM). Its key innovation lies in the ability to integrate metadata (e.g., industry sectors) and their corresponding words into each document before initiating the automated process of discovering topics and estimating their likelihood of occurrence in a document. Technically speaking STM is based on LDA but includes covariates (i.e. idiosyncratic language within a subset of the documents) and covariances between topics (see Roberts et al., 2019). Figure 1 highlights the formulized problem of the LDA as well as the proposed solution by the STM.

The text corpora (corpus A and B) in Figure 5.1 illustrate examples of our later-used data set. The identified words defining the topics by LDA correspond to the already known sectors – corpus A is provided by a firm in the healthcare sector and corpus B by a firm in the residential sector. At the same time, both corpora address the topic "Legal & Litigation Risk" which is not identified by LDA but by STM as the common topic. Thus, STM allows extracting common factors across documents by excluding the already known metadata (e.g., healthcare and residential) and their corresponding words. Consequently, the industry-specific vocabulary distracts the LDA and CTM from extracting common risk factors.

This research delves into the question of whether risk topics, extracted from unstructured text data using advanced machine learning methods, yield more effective results in explaining return volatility compared to older methods that focus on text length and readability, or overlook the correlation between topics and words in documents. Our aim is to contribute to the growing utilization of text data in accounting and financial research. Additionally, we seek to shed light on the unresolved question of whether the capital market perceives it positively (i.e. risk-minimizing) when firms provide more comprehensive disclosures about risks in their documents.

We find that LDA and CTM are distracted from extracting common risk factors and can

Figure 5.1: Stylized Illustration of LDA and STM


This figure shows text corpora provided by a firm in the healthcare sector (corpus A) and a firm in the residential sector (corpus B). Both corpora address the topic "Legal & Litigation Risk" which is identified by STM as the common topic. Words associated with the topic "Legal & Litigation Risk" are highlighted in yellow. Words associated with the LDA topic "Health Care" are highlighted in blue. Words associated with the LDA topic "Residential" are highlighted in red. Words associated with either the metadata covariate "Health Care" or "Residential" are in bold.

therefore hardly be linked to the pricing behavior of investors. Contrary, the STM-extracted risk factors are statistically significantly associated with volatility and consequently, with the risk perception of investors. Simple methods of measuring risk by counting words are of minor importance but a hybrid model – combining machine learning with a word-counting factor – explains best the return volatility within our dataset. Our results mostly support that executives use disclosures to resolve firms' known risk factors or give more facts about known risk factors and thus, reduce risk perceptions on the market. In a supplementary analysis, we discover supporting evidence for extending our findings also to sectors with heterogeneous business models and lower investor perception.

Our findings carry implications for the accounting and finance research community, as well as for industry practices. By leveraging advanced machine learning-based methods that consider the covariate and covariance aspects of words, we can effectively identify risk-relevant factors from textual data. This capability enables us to incorporate information into our risk analyses that would otherwise be hard to include, given the limitations of human capacity to process thousands of documents. The observed predominantly risk-reducing effect associated with a higher likelihood of occurrence of risk topics may serve as motivation for firm executives to enhance the discussion of risk factors in their disclosures. This could potentially clarify the impact of risks on the firm's future development.

Our study contributes to the literature in various ways. To the best of our knowledge, this is the first study applying STM to the accounting and finance domain while also benchmarking it with LDA and CTM. We show, that the so-far predominantly used LDA is biased by the used idiosyncratic language within an industry reflecting rather the already known operative line of business or business models than significant topics of a document. This is also true for CTM, the advanced LDA algorithm, which is the most suitable benchmark for STM although it is not used in the economic literature so far. In addition, our analysis provides insights into whether and how information is incorporated into the pricing process. By introducing STM, we apply the algorithm to the important but rather neglected industry sector of REITs (Real Estate Investment Trusts). This industry is an appealing testing ground for multiple reasons. First, while the sector is described by relatively homogenous business models and firm characteristics, its firms invest in different property types (e.g., healthcare, residential). This sample allows us to show that even in a sample favorable to LDA, it is more likely to find already known topics (i.e. property types) rather than uncovering common risk factors across the entire sector. In contrast, STM has the capability to directly discern these shared risk factors. Second, REIT's managers must turn to the capital markets repeatedly to raise funding for new projects since they have very limited cash reserves due to regulation requirements. This regulation incentivizes REITs to be transparent, disclose their fillings with a relatively high quality, act for the long-term, and sustain investor trust. Third, REITs are distinguished by substantial investments in fixed assets, resulting in relatively stable cash flows. This stability appeals to institutional investors, equipped to navigate through lengthy and intricate disclosures more effectively. Therefore, it is reasonable to anticipate observable stock market reactions based on the disclosed information for this sector.

The remainder of the paper is organized as follows. Section 5.2 discusses related literature on mandatory risk disclosures and develops hypotheses. Section 5.3 explains the textual analysis procedures (i.e. LDA, CTM, and STM) and the empirical model, while Section 5.4 introduces the data used and describes the variables. The empirical results are reported in Section 5.5, and Section 5.6 concludes.

## 5.2 Previous Literature and Hypotheses Development

### 5.2.1 Textual Analysis in Accounting and Finance

Fueled by the rise of computational power and the tremendously increasing online availability of text, a growing body of literature in accounting and finance has focused on computer-based techniques to find and quantify information revealed in qualitative disclosures (e.g., media news, public corporate disclosures, analyst reports, and internet postings). Within the finance research, probably Tetlock (2007) provides the pioneering study by employing automated content analysis to extract sentiment from the Wall Street Journal's column "Abreast of the Market" by counting specific words. He demonstrates, that media pessimism induces downward pressure on market prices and leads to temporarily high market trading volume. Thereafter, multiple studies analyze how sentiment predicts the reactions of financial markets. For example, Garcia (2013) processes finance news from The New York Times and provides evidence that positive words also help to predict stock returns. Tetlock et al. (2008) analyze firm-specific news from the Dow Jones News Service and The Wall Street Journal and prove that negative words convey negative information about firm earnings beyond stock analysts' forecasts and historical accounting data. Antweiler and Frank (2004), Das and Chen (2007), and Chen et al. (2014) investigate the textual sentiment of internet messages. Hereby, Antweiler and Frank (2004) find evidence that the amount of message posting predicts market volatility and trading volume. Chen et al. (2014) figure out that the fraction of negative words contained in articles published on Seeking Alpha negatively correlates with contemporaneous and subsequent stock returns. Das and Chen (2007) make assumptions about the relationship between textual sentiment and investor sentiment when interpreting textual sentiment or tone of internet messages as small investor sentiment. They link market activity to small investor sentiment and message board activity. Regarding the studies addressing corporate disclosures, textual sentiment has been found to be positively related to abnormal stock returns (e.g., Feldman et al., 2010; Jegadeesh and Wu, 2013; Chen et al., 2014), subsequent stock return volatility (e.g., Loughran and McDonald, 2011, 2015), and future earnings and liquidity (e.g., Li, 2010).

Further research investigates the readability of corporate disclosures and provides evidence that lower annual report readability is associated with increased stock return volatility (Loughran and McDonald, 2014), lower earnings persistence as well as higher earnings surprise (Li, 2008; Loughran and McDonald, 2014), larger analyst dispersion (Lehavy et al., 2011; Loughran and McDonald, 2014), and lower trading due to a reduction in small investor trading activity (Miller, 2010). Only recently, Cohen et al. (2020) use sentiment and multiple similarity measures to show that changes to the language and construction of corporate disclosures impact stock prices with a time lag. The authors conclude that investors need time to process complex and lengthy disclosures.

Other recent papers try to develop new machine-learning-based methods for textual comprehension and topic extraction in financial economics. Among them, Cong et al. (2019) generate textual factors using neural-network language processing and generative statistical modeling which can be used for macroeconomic forecasting and factor asset pricing. Kelly et al. (2021) develop a high-dimensional selection model that focuses more on a phrase than the frequency of repetition. They apply it not only to U.S. congressional speeches but also to estimate macroeconomic indicators using newspaper text. Li et al. (2021) create a culture dictionary based on the word embedding model and earnings call transcripts and show that an innovative culture is wider than the usual way to measure innovation. Das et al. (2022) present an automated approach to generate wordlists that have a comparable performance to traditional lists on machine learning classification tasks.

This study contributes to the emerging literature on textual analysis by adopting a new perceptive based on an often applied method. Instead of focusing on the tone conveyed through the narrative, the complexity of the language, or document similarity, we extract topics out of corporate risk disclosures using machine learning approaches.

### 5.2.2 Textual Analysis of Risk Disclosures

The literature has applied various methods to assess a firms' risk disclosure, which we classify in two categories. Within the first and more straightforward category, the entire risk disclosure is observed as a unit and its "size" is considered as a proxy for risk. Within the second and more sophisticated category, the individual risk itself comes to the forefront. The former category comprises studies that count risk keywords (e.g., Li, 2006; Kravet and Muslu, 2013) or rely on the total length of the risk section (e.g., Campbell et al., 2014; Nelson and Pritchard, 2016 ) to measure firms' risk disclosures. Hereby, increased levels of forward-looking disclosures (e.g., risk disclosures) are linked to an increased trading volume (Kravet and Muslu, 2013), and lower future earnings and stock returns (Li, 2006). The result for stock return volatility is not so clear; the majority find a decreasing effect (e.g., Beyer et al., 2010; Muslu et al., 2015), whereas others an increasing effect (e.g., Kravet and Muslu, 2013; Campbell et al., 2014). Common to the studies using straightforward approaches is that they can process a large number of textual documents which is beyond human capacity, but they obviously lose a lot of information written in the text.

Only recently and within the latter category, researchers have started to focus more on the written content by making use of machine learning approaches to identify and quantify the individual risks. In this context, the unsupervised machine learning approach Latent Dirichlet Allocation (LDA) is most popular for finding the individual risks discussed in firms' filings. The outcomes are manifold: Israelsen (2014), for example, examines the association between the risks disclosed in Item 1A and stock return volatility, as well as betas of the Fama-French Four-Factor model. Employing a variation of the LDA, Bao and Datta (2014) analyze whether and how risk disclosures affect investor risk perceptions. Their findings indicate that some risk factors increase or decrease investor risk perceptions, and thus lead to higher or lower post-filing return volatility, whereas the majority have no effect at all. Gaulin (2019) uses disclosed risk factors to analyze disclosure habits and suggests that managers time the identification of new risks, as well as the removal of previously identified ones, to match their expectations of adverse outcomes in the future. Recently, Lopez-Lira (2020) demonstrates the importance of risk disclosures by providing a factor model that uses only identified firm risk factors to explain stock returns and performs as least as well as traditional models, without including any information from past prices. The key benefit of machine learning approaches is that they do not require predefined rules (i.e. a priori determined keywords) to identify risk factors. Instead, risk factors or general speaking topics derive naturally from fitting the statistical model to the textual corpus, based on word co-occurrences in the documents.

### 5.2.3 Hypotheses

Common to all approaches, whether straightforward or sophisticated, is that they attempt to quantify qualitative information in disclosures without the need for a human being to read them. However, quantifying risk disclosures is quite challenging given that firms neither reveal the likelihood that a disclosed risk will ultimately affect the company, nor the quantified impact a risk might have on the firm's current and future financial statements. Thus, forward-looking risk disclosures might inform the reader, for the most part about a vague range, but certainly not the level of future performance (Kravet and Muslu, 2013). Nevertheless, assuming that firm executives truthfully report their views under SEC scrutiny and penalty of litigation, it can be argued that detailed firm-specific information is provided in 10-K filings. In fact, previous research (e.g., Kravet and Muslu, 2013; Bao and Datta, 2014) finds a stock market reaction of risk disclosures confirming its informativeness.

Recognizing that management's discretion entails considerable leeway in deciding which information about a risk factor is disclosed and how much of the filing is allocated to a particular risk-factor topic, we assume that these probabilities of topics provide valuable information on how companies assess the extent of the risks. Accordingly, the topic probabilities in the filings derived from unsupervised machine learning algorithm, mostly by the Structural Topic Model (STM), could serve as a proxy for risk beyond the level of previous straight-forwarded proxies (e.g., word count, text length), allowing investors to quantify the information provided in narrative form.

**Hypothesis 1:** *The probabilities of risk topics in textual reports – derived from the STM model – present significant explaining factors in empirical models analyzing investor risk perception.*

The nature of risk disclosures is that it explains but does not necessarily resolve uncertainties. Thus, theoretic models (e.g., Kim and Verrecchia, 1994; Cready, 2007) see the possibility that risk disclosures increase or decrease investors' risk perceptions. Kravet and Muslu (2013) define three opposing arguments. The first argument suggests that investor risk perceptions remain unaffected since risk disclosures are vague and use boilerplates because managers are likely to report all possible risks and uncertainties without considering their impact on businesses just to be on the safe side (null argument). The second argument states that risk disclosures reveal unknown risk factors or risk-increasing facts about known risk factors causing diverging investor opinions and increasing risk perceptions (divergence argument). The third argument assumes that executives use disclosures to resolve firms' known risk factors or give more facts about known risk factors and thus, reduce risk perceptions (convergence argument). This ambiguity is supported by the mixed results in empirical research (see the previous subsection), whereas the majority find resolved uncertainties (i.e. lower volatility) in response to corporates' disclosures. Since we are able to extract risk topics at a higher level of granularity than previous straight-forwarded risk proxies, we assume that we find all three risk perceptions (null, convergence, and divergence argument). Knowing that the annual frequency of 10-Ks is from the legal and practical perspective inappropriate to discuss new risks, we assume that the majority of disclosures resolve known risk factors and contingencies and formulate our next hypothesis as follows.

**Hypothesis 2:** *The majority of the risk factors present a risk-reducing effect, supporting the convergence argument.*

## 5.3 Model Design

### 5.3.1 Textual Analysis with Machine Learning: LDA and CTM

Topics derive naturally from fitting the statistical model to the textual corpus based on word co-occurrences in the documents. Thus, this procedure eliminates subjectivity that would otherwise be introduced by predefined wordlists, and yet provides more informative results than straight-forwarded approaches, which can still be interpreted economically. The Latent Dirichlet Allocation (LDA) is the most frequently used topic modeling approach in the scientific literature; it is borrowed from genetic science (Pritchard et al., 2000) and transferred to machine learning by Blei et al. (2003). It is a mixture model, generating the probabilities of co-occurring topics (subpopulation) within the distribution over all words (population). Put simply, the mixture model aims to break documents down into topics, whereby the words within each topic co-occur most frequently. Thus, applying the LDA to a textual corpus results in two data structures in the output. The former presents the probability of appearance of each topic in each document $\theta_d$, with documents being indexed by d. The latter lists a set of words and their probabilistic relation with each of the extracted topics $\beta_k$, with topics being indexed by $k$. LDA comes with the limitation that the used Dirichlet distribution assumes almost uncorrelated topics. However, they are likely correlated in reality since particular topics occur at the same time. For an illustration, see Figure 1 in our Introduction. These covariances are addressed by Blei and Lafferty (2007) in their Correlated Topic Model (CTM) method. Also, the CTM is a mixture model but replaces the Dirichlet distribution with a logistic normal distribution in order to include the covariance structure among topics. Surprisingly, it is not very often applied even if Blei and Lafferty (2007) show the theoretical and practical importance of a covariance structure by using 16,351 Science articles. They find that CTM is always superior to LDA for altering the number of topics from 5 to 120.[2]

### 5.3.2 Textual Analysis with Machine Learning: STM

The Structural Topic Model (STM) by Roberts et al. (2019) goes even one step further and incorporates metadata of pre-specified covariates (industry-specific vocabulary), not only covariances; see Figure 1 and discussion in the Introduction for healthcare vs. residential. Again, it remains a mixture model based on a logistic normal distribution, so that it corresponds to CTM if covariates are ignored. The covariates cover for topical prevalence, topical content, or both. The former affects how much a topic is discussed ($\theta_d$), whereas the latter affects which words are used to discuss a particular topic parameter ($\beta_k$) (Roberts et al., 2014). In order to allow the algorithm to find topics beyond the already known identifiers, we include property types as metadata covariates. Contrary to the LDA, where the topic proportion $\theta_d$ is drawn from a Dirichlet distribution, the STM employs a logistic-normal generalized linear model which is based on document covariates ($X_d$). Thus, the frequency with which a topic is discussed that is common across all documents in the LDA is now affected by the observed metadata, as indicated by the following equation:

$$\overrightarrow{\boldsymbol{\theta}_d}|\mathbf{X}_d\gamma, \Sigma \sim \text{LogisticNormal}(\mu = \mathbf{X}_d\gamma, \Sigma) \tag{5.1}$$

where $\mathbf{X}_d$ is a 1-by-$p$ vector, $\gamma$ is a $p$-by-$(K-1)$ matrix of coefficients, and $\Sigma$ is $(K-1)$-by-$(K-1)$ covariance matrix.

Whereas LDA assumes that word proportions within each topic ($k$) are represented by

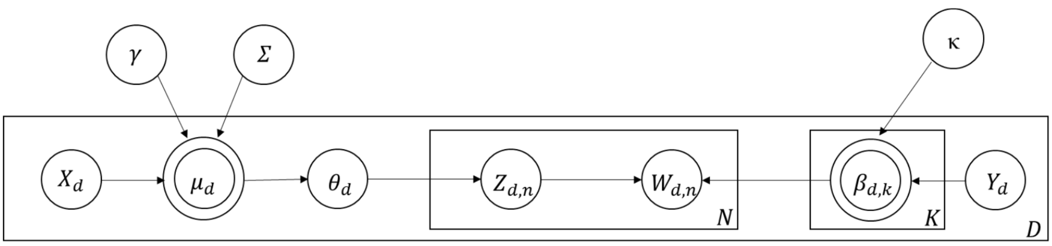
[2]This paper provides only an overview of LDA and CTM); for deeper insights, we refer to the original papers by Blei et al. (2003), Blei and Lafferty (2007).

the model parameter $\beta_k$, which is identical for all documents ($d$), STM allows that the words describing a topic vary. Specifically, given a document-level content covariate $y_d$, the STM forms document-specific distributions of words representing each topic ($k$) based on the baseline word distribution ($m$), the topic-specific deviation $K_k$, the covariate group deviation $K_{y_d}$, and the interaction between the two $K_{y_d,k}$. The following equation provided by Kuhn (2018), and based on Roberts et al. (2019), summarizes this relationship as follows:

$$\beta_{d,k} \propto \exp(m + K_k + K_{y_d} + K_{y_d,k}) \tag{5.2}$$

Figure 5.2 presents the STM in the common plate notation for topic modeling. Hereby, one "plate" exists for each document ($D$) and its associated topic distribution ($\theta_d$) in the textual corpus. The inner plate, comprising topics ($Z_{d,n}$) and words ($W_{d,n}$), is replicated for each of the $N$ words in the document. Analogously, the plate including the model parameter $\beta_{d,k}$ is replicated for each of the $K$ topics in a textual corpus (Blei, 2012; Kuhn, 2018).

Figure 5.2: Structural Topic Model

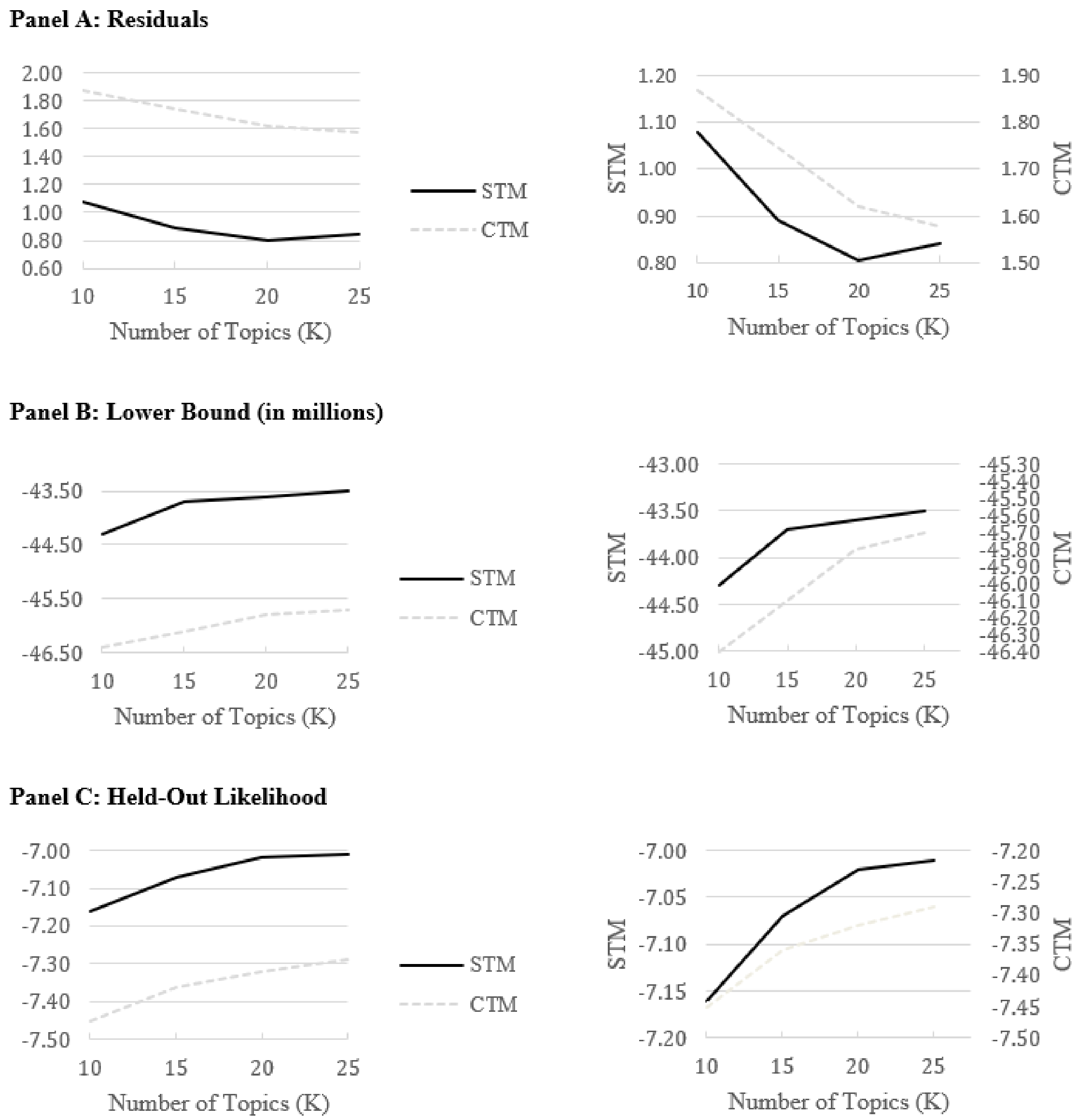



Structural Topic Modeling, in plate notation (following Roberts et al., 2019)

After pre-processing, we estimate the STM, based on a variational Expectation-Maximization algorithm. The maximum number of iterations is set to 100, so that convergence is always reached before this threshold.

We run various tests checking whether the higher flexibility of STM corresponds to a better fitting among the approaches. The better the topic identification works the higher the probability that the topics may help to explain the investors' risk perception. In a pre-test, we run a technical comparison for CTM and STM similar to Blei and Lafferty (2007) comparison for LDA and CTM. We fit a smaller collection of documents of our later-used dataset to a varying number of topics (between 10 and 25) and calculate the residuals, lower bounds, and log likelihoods of the held-out data. The better a model fits the lower are the residuals and the higher are the lower bounds as well as the probability of the held-out data. All three measures indicate a better fit for STM for the full range of topic numbers (see Figure 5.3, Panel A-C). Additionally, topic modeling requires an a priori determination of the number of topics to be generated. All comparison measures indicate directly or converge to a topic number of 20 as the best number. Consequently, we extract 20 individual risk factors from the risk disclosures.

Figure 5.3: Structural Topic Model Comparision




This figure shows the standard criteria for comparing different topic models, namely residuals regarding the text corpora (Panel A), lower bound (Panel B), and held-out likelihood with a standard of 20 percent (Panel C). On the left hand side and identical scale, the STM outperforms the CTM on our data set. The right side shows two different scales for each model to clarify the turning points of optimization process for a different number of topics ($K$) within each model.

Based on the superiority of CTM over LDA (see Blei and Lafferty, 2007) and STM over CTM as well as LDA (see Roberts et al., 2014 and our pre-test), we assume that STM is most suitable to extract topics explaining the investors' risk perception. In our later analysis (Subsection 5.5.6), we compare the explanatory power of all three approaches to explain the investors' risk perception.

### 5.3.3 Topic Identifications: Pre-steps

Several preprocessing steps are necessary before running the topic models. First, we parse the downloaded 10-K filings to extract the risk report part from the entire document.[3] In addition, we clean the data by removing spaces, numbers, and punctuation. Second, relying on the "stop word" list provided by Grün and Hornik (2011) and Roberts et al. (2019), words like 'and', 'or', and 'the' are removed from the corpus, since they lack semantic information, and thus do not help to identify the topics. Third, we eliminate words appearing in fewer than 20 disclosures to avoid their influence. On the one hand, this threshold (20 occurrences) rules out words occurring solely in 10-K filings of one particular firm (e.g., the firm names), since we have 14 years of observations. On the other hand, low-frequency words cannot be clearly assigned to an individual topic, and thus introduce noise into the process. Excluding them ensures the robustness of the algorithm, and in addition, increases computational speed (Papilloud and Hinneburg, 2018). Unlike Roberts et al. (2019), we do not stem the words and instead use explicit word inflections for reasons of interpretability. This abandonment is supported by Schofield and Mimno (2016), who find that stemming does not improve topic stability, and possibly even degrades it.

### 5.3.4 Topic Identifications: Risk Factors Labeling

Although topic-modeling approaches classify textual data without further instruction by the user, the topics created by the algorithms (LDA, CTM, and STM) do require an interpretation. More specifically, a human being has to assign labels with an assessment of the most plausible content to the algorithm-based topics, which are only equipped with a number and a set of words most frequently associated with each topic. In order to label the risk-factor topics appropriately, we read a random sample of disclosures comprising 2% of the overall sample. Two of us then independently reviewed the word lists comprising the 20 highest associated terms for each risk-factor topic. As recommended by Roberts et al. (2019), we also inspected documents that were considered to be highly associated with a specific topic, and thus, are expected to represent the topic most clearly. We discuss the associated words selected labels in Subsection 5.5.3. Table A.1 in Appendix A presents the full list of the 20 highest associated words for each risk factor topic for STM and the

[3] To apply topic models, we use the programming language R (version 4.0.2) and the corresponding packages topicmodels and STM, authored by Grün and Hornik (2011) and Roberts et al. (2019); we use the edgarWebR package for parsing.

corresponding name; Table B.1 in Appendix B does it for LDA.

### 5.3.5 Risk Model Specification

Drawing on prior research investigating the associations between risk disclosures and stock return volatility (e.g., Kravet and Muslu, 2013; Bao and Datta, 2014), we construct a model that incorporates various potential risk factors. These factors include textual data obtained through machine learning methods (e.g., Israelsen, 2014; Bao and Datta, 2014; Muslu et al., 2015), textual data derived from simple counting methods (e.g., Li, 2008; Lehavy et al., 2011; Campbell et al., 2014), changes in performance, ownership, trading volume, firm-specific and market-wide risk measures (e.g., Kim and Verrecchia, 1994; Bamber and Cheon, 1995; Kravet and Muslu, 2013), and REIT-specific risk factors taking into account that REIT's returns have become sensitive to factors influencing small-cap stocks (e.g., Ooi et al., 2007; Bond and Xue, 2017). With the exception of the first category, all other variables are grouped within the control variables category. A detailed description of the independent variables is provided in Subsection 5.4.3.

To assess whether the probabilities of appearance of the extracted risk factors helps to explain the perceived risk on the stock market, we regress whose frequencies (Freq_Topics) on the firms' stock return volatility (Vola) by using the following two-way fixed-effects regression model:

$$\text{Vola}_{it} = \beta_0 + \beta_1 \text{Freq\_Topics}_{it} + \beta_2 \text{Controls}_{it} + a_i + \lambda_t + u_{it} \tag{5.3}$$

where $i$ denotes the firm, and $t$ the year. In addition to the vector of the distribution of the individual risk topics (Freq_Topics), the regression equation includes a vector of control variables (Controls). The parameters $a_i$ and $\lambda_t$ incorporate the unobserved firm and time effects, and $u_{it}$ is the error term. The two-way fixed effects model incorporates the specific differences between individuals in a micro panel dataset covering roughly 14 years Wooldridge (2010). To produce consistent, efficient, and unbiased estimates, we examine whether any of the model's assumptions are violated. Employing Variance Inflation Factors (VIF) to check for multicollinearity, we find values greater than 5 for Topic #7, Topic #11, Topic #14, and Topic #18. Thus, these topics are explained by all other topics by at least 80% each, so we exclude these topics from our later analysis. In doing so, we apply a stricter threshold often applied (greater than 10 or 90% is explained by the other topics), since we prefer to have a parsimonious model with fewer variables, which make it less susceptible to spurious relationships and harder to verify that our topics are significant. The VIFs of the remaining variables are within the range of 1.1 and 4.4.

## 5.4 Data

### 5.4.1 Data Source and Sample

To test our hypotheses, we combine multiple datasets: (1) investors' risk perception proxied by stock return volatility from CRSP, (2) the text corpus given by the Risk Factor report (Item 1A) of the annual 10-Ks obtained from the Electronic Data Gathering and Retrieval (EDGAR) database, and (3) firms' financial and accounting fundamentals obtained from Compustat or Thomson Reuters.

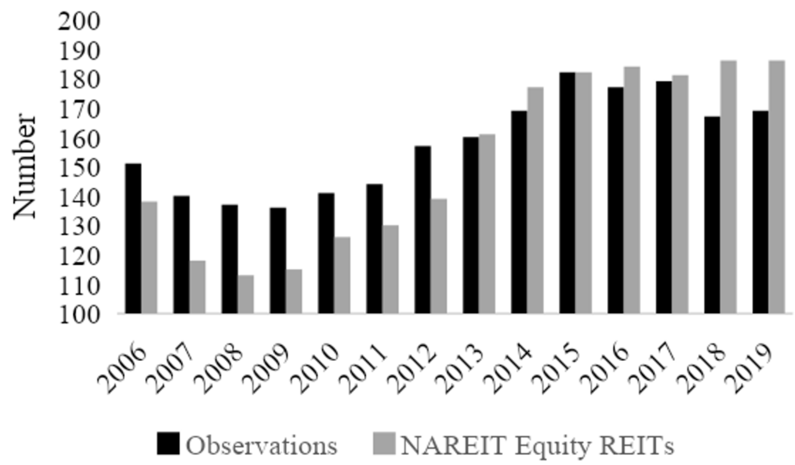
Our sample begins with the earliest date when 'Item 1A. Risk Factors' was available (December 1, 2005)[4] and extends through the fiscal year-end 2019. To mitigate potential confounding factors related to the pervasive risk associated with the COVID-19 pandemic, we concluded our sample in 2019. This deliberate decision ensures the avoidance of any overlap with the pandemic's impact on our analysis. In contrast to other studies focusing on the entire firm-year sample available from EDGAR database, we limit our examination to a single industry, namely the REIT industry, for multiple reasons. First, while the sector is characterized by relatively homogenous business models and firm characteristics, different investment foci in property types (e.g., healthcare, residential) are salient and distract the LDA from extracting common risk factors (see Figure 5.1). Second, REITs' 10-Ks guarantee a relatively high disclosure quality, given their high dividend payout requirement of at least 90% of their taxable earnings. Consequently, they have a very limited cash reserve and must turn to the capital markets repeatedly to raise funding for new projects. This regulation incentivizes that REITs are transparent, act for the long-term, and sustain investor trust (Danielsen et al., 2009; Doran et al., 2012; Price et al., 2017). Third, the real estate industry is characterized by a well-known business model – high investments in fixed assets generate relatively constant cash flow for their investors. This property is attractive for institutional investors since the early 1990s as shown by others (e.g., Ling and Ryngaert, 1997; Lee et al., 2008). This type of investor can process lengthy and complex disclosures easier, so it is reasonable to assume that we can observe stock market reactions based on the disclosed information. Furthermore, investors must intensively monitor this type of industry for adverse information and outcome (risk) since their capital is tied in fixed assets,

[4]Actually, there is a second risk section in the 10-K. Item 7A lists "quantitative and qualitative disclosures about market risk" which are relevant for a company (e.g., interest rate risk or foreign currency exchange risk). However, Item 7A differs from Item 1A in that this section not only names but additionally quantifies the impact of the individual risk factors on future firm performance. Thus, managers usually use numbers to describe how risk factors affect firms' filings in this section. Additionally, with an average length of only 6,680 words, Item 7A is just a tenth of the average length of Item 1A. Given that our method focuses on textual data, i.e. the words used to qualitatively describe relevant risks, we exclude Item 7A from the main analyses. This is essential because topic models cannot take numbers into account and shorter documents decrease the robustness of the topic model because it "learns" less from the data (Papilloud and Hinneburg, 2018). However, for reasons of completeness, results for Item 7A are presented in Appendix D.

which do not have high future expectancies regarding new technologies or where losses can be compensated by new exceptional growth opportunities. In addition, institutional investors are rarely driven by noise trading or herding behavior, which irrationally influence the stock prices. However, institutional investors apply often passive investment styles with a buy-and-hold strategy and a long-term horizon (see e.g., Chung et al., 2012; Devos et al., 2013). Consequently, positive news keeps the ownership of institutional investors constant whereas negative news may not lead to a direct divestment if they are not severe.

Our sample consists of all Equity REITs present in the FTSE NAREIT All REITs Index at any point of time during the sample period. Mortgage REITs are excluded from the analysis because they differ in characteristics (e.g., underlying asset, risk structure), exposed risk factors, and are recognized as more difficult to value for external investors (Buttimer et al., 2005). Out of the 246 distinct firms, 25 consistently remain in the index throughout the entire sample period, while 221 firms either enter, exit, or both enter and exit the sample. After including control variables, our subsequent regression analyses are based on 199 distinct firms. Figure 5.4 displays the sample composition of the 10-Ks over years; our observations mostly follows the number of REITs included in the FTSE NAREIT All REITs Index over the same time period. For some years, the observations exceed the number of index constituents, since we include a firm in our sample if it was a constituent at any point during the period. We thus address survivorship bias and index effects such as greater investor attention to firms listed in an index. Firm-year observations that lack necessary control variables or stock prices are excluded, resulting in an overall sample of roughly 1,230 observations consisting of 199 unique firms. The limiting variables are the control variables obtained from CRSP and Compustat and not the risk factors extracted from the 10-K filings (see Table 5.1 for more details about $N$).

Figure 5.4: Sample Distribution over Years




This figure shows the number of observations included in the sample and the number of Equity REITs present in the FTSE NAREIT All REITs Index over years.

### 5.4.2 Investors' Risk Perception

The dependent variable of interest is the perceived risk on the stock market measured by the return volatility after the filing date using the daily closing prices from CRSP. It is unclear how long it takes until investors read 10-Ks, and new information is incorporated into price changes. Thus, we apply multiple testing periods for firms' stock return volatility after the 10-K filing is published – a 5, 40, and 60 trading-day period. The 5 trading-day period gives investors enough time to read, interpret and react to disclosures while being short enough to minimize the influence of other disruptive events that may also affect volatility. The 60 trading-day period accounts for investors comparing risk factors disclosed in 10-Ks to changes disclosed in quarterly reports (10-Qs).[5] We calculate volatility as the standard deviation of daily log returns extrapolated to the 5, 40, and 60 trading-day periods after the 10-K filing day.

$$\text{Vola}_T = \sqrt{T} \times \sqrt{\frac{\sum_{t=1}^{T} \left(\ln(1+r_t) - \mu_T\right)^2}{T-1}} \tag{5.4}$$

where $T \in \{5, 40, 60\}$.

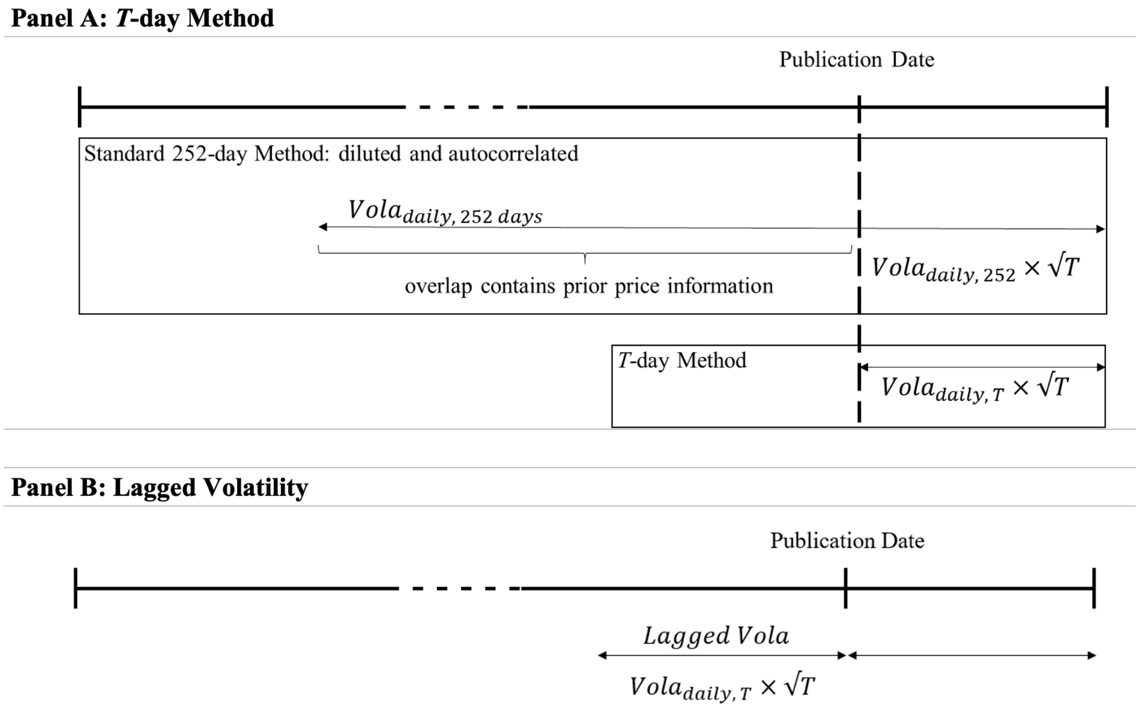
In contrast to the common approach using a 252 trading-day volatility, our procedure concentrates on the volatility induced by the information released in the 10-K. A 252 trading-day window may be too diluted since it includes price-sensitive information over the entire prior trading year. Thus, past information that is already known and has been incorporated into prices, would be extrapolated to our testing period. Additionally, the standard deviation over a 252 trading-day window would cause autocorrelation problems after adding a control variable for the lag volatility for the days before the 10-K filing date, since the majority of the time window overlap. We illustrate this in Figure 5, Panel A.

By contrast, our method surveys volatility, starting from the filing publication date until the end of the processing period. To account for the problem of autocorrelation due to volatility clustering around specific dates and other influencing filing events, we include a lagged volatility measure in the model as a control variable. This variable gauges the standard deviation textitT days before the publication date, see Figure 5.5, Panel B. We also attempted to utilize alternative risk measures, such as implied volatility based on options and credit default spreads. However, we faced difficulties in acquiring an ample number of observations for our subsequent analyses, and consequently, we have retained volatility as our risk measure.

Our primary influencing variables of interest are the frequencies of the machine learning-extracted risk factors discussed in corporate disclosures (Freq_Topic). We start with the

[5] We additionally analyze the 10 and 20 trading-day periods. As expected, the results are in the intermediate ranges.

Figure 5.5: Volatility around Publication Date




This figure contrasts the common approach using the 252 trading-day volatility to calculate current volatility to our $T$-day method (Panel A). Panel B shows the lagged volatility measure.

STM and verify our results using CTM and LDA; their calculations are described in Section 5.3. To control for information beyond the risk factors, a set of control variables is included. Besides firm characteristics, performance, and risk measures, we additionally consider textual 10-K characteristics that previous research has revealed as determinants of return volatility. We describe all control variables below, and provide more specific definitions, including Compustat data items, in Table A.3 in Appendix A. We cluster the controls into two subsets: 1) accounting-based/market-based and 2) textual.

For the first of the two, we include the REIT-specific performance measure Funds From Operations per share (FFO/Share), to incorporate the real-estate-specific income characteristics. We calculate FFO by following NAREIT's guideline: the sum of net income, amortization & depreciation, and the difference of the net of gains and losses originated by the sale of assets from the net income. Since FFO/Share is a performance measure, we expect a negative coefficient sign. The variable Size, measured as the natural logarithm of the firm's total assets, controls for Fama and French (1993) finding that small firms are more volatile than large firms; we expect its coefficient to be negative. Leverage is a common proxy for firm risk, so we expect the variable to be positively related to volatility. The motivation for the next two factors is purely at the operating level – the annual change in revenue (ΔREV) as well as sales growth (Sales_Growth). ΔREV is defined as current sales or rental income less prior year sales. Sales_Growth is calculated as REV scaled by total assets in the previous year. We expect a positive influence from both variables. Among the market-based controls, Beta proxies the firm risk similar to Leverage, so that we expect a positive nexus to volatility. Book-to-Market (BTM) is calculated as the book value of equity, scaled by the market capitalization of equity. Our expectations of BTM are ambiguous. On the one hand, the coefficient could be positive if market participants have little confidence in the future prospects of a firm. On the other hand, the coefficient on BTM will be negative if growth opportunities are positively related to firm risk (Fama and French, 1993; Campbell et al., 2014). The standard control variables, BTM and Size (natural logarithm of total assets), are employed independently of the Fama-French methodology. This is crucial, as early analyses of REITs revealed that their return characteristics, predominantly influenced by stable cash flows, bear a closer resemblance to bonds than to stocks (Karolyi and Sanders, 1998). Consequently, it comes as no surprise that Fama and French (1993) excluded REITs, along with other financial firms, from their dataset. However, the REIT landscape had undergone significant structural changes in the early 1990s, reshaping them into instruments that bore a closer resemblance to stocks (Glascock et al., 2000). This transformation prompted a shift in research, revealing that REIT returns became increasingly responsive to the same factors influencing small-cap stocks and specific drivers within the real estate sector (Clayton and MacKinnon, 2003). As a result, contemporary research has adopted Size and Book-to-Market as risk factors to elucidate the dynamics of REIT returns (e.g., Ooi et al., 2007; Bond and Xue, 2017).

Additionally, we include the stock return volatility (Lag_Vola) for the corresponding $T$ trading days before the 10-K filing date, to control for positive volatility correlation in the short-run and information released in other outlets as the 10-K. We expect a positive relationship between the pre- and post-filing-date volatility. We also add the stock return volatility of the S&P 500 ($Vola^{S\&P}$) for $T$ trading days before the 10-K filing date, as a benchmark for changes in the general market volatility and expect a positive coefficient. The change of a firm's average daily trading volume from the symmetric period of $T$ trading days before to after the 10-K is filed ($\Delta$Volume), serves as a factor of the economic interactions in the financial market. In addition to stock price changes, trading volume conveys important information about the underlying economic forces. We expect that higher changes in the trading volume go in line with higher volatilities. Furthermore, the percentage of institutional ownership (IO), defined as the sum of shares held by institutional investors, divided by the shares outstanding, is incorporated as obtained from Thomson Reuters. Institutional investors have higher capacities to process 10-Ks, and thus could react in a timely manner to the disclosed information, causing a positive coefficient on IO. Conversely, the coefficient could be negative if the long-term orientation of sophisticated investors is predominant and they behave inertially.

For the second subset of controls, we include straightforward textual content measures of previous research. In line with Campbell et al., 2014, who show that the number of words is positively related to stock return volatility, we incorporate the natural logarithm of the total text length of the risk sections (Text_Length). Additionally, we follow Li (2008) and Lehavy et al. (2011) and incorporate the readability measured by the Gunning fog index (FOG) to account for higher information-processing costs of complex language.

### 5.4.3 Descriptive Statistics

Table 5.1 presents descriptive statistics for all variables. The STM's frequencies for the risk factor topics (Freq_Topic) sum to 1 within each document but not over all documents. We observe rather small topic frequencies for Item 1A by looking at their means; the highest is around 7.6% for Topic #16 "Property", the lowest for Topic #14 "REIT Status" at 2.2%. An equal distribution over all topics would result in 5% (1/20) for each topic. Focusing on the extreme values (Min and Max), we see that all topics constitute the core of any 10-K filing (lowest Max is 99.8%) or are practically not discussed (highest Min is 0.0004%). The distribution of all topics is extremely skewed so that we use a log transformation of these factors in our later regressions. By using the Shapiro and Wilk's test, we can conclude that the logs of the risk factors are normally distributed (Royston, 1982). The correlation coefficients among the logged risk factors are not higher/lower than 0.47/-0.63 (Table A.4 in Appendix A). Thus, the topics have no direct linear relationship, but as shown in Section 5.3, the VIF for 4 topics (#7, #11, #14, and #18) is high. Thus, these topics are explained substantially by a linear combination of the other topics, so that we exclude them from our later analysis and restrict our model to topics that mostly convey new information.

The classical fundamentals in the control set show the common values and are comparable with other REIT studies (e.g., Doran et al., 2012; Price et al., 2017; Koelbl, 2020). The percentage of institutional ownership (IO) is on average 76%, with an interquartile range from 64% to 95%. The restriction to shares outstanding in the denominator results in extreme ratios of greater than 1 for a few observations where the institutional investors own more than the outstanding shares. The Text_Length counted by words included in Item 1A varies in the interquartile range from 38,302 to 87,198. The extreme values are surprising; the shortest Item 1A has only 36 words, whereas the longest has 516,463 words. The low number of words is driven by small REITs which do not have to publish risk reports according to the SEC requirements; see Example 1-2 in Table A.5 in Appendix A. In total, we have only 8 reports with fewer than 1600 characters (including stop words) for their reports; see Example 3 in Table A.5 for a short Item 1A with 374 words. The readability of the text, as measured by the Gunning fog index, is complex. The interquartile range is close with 21.7 to 23.3 and higher than the reading level of a colleague graduate given

Table 5.1: Descriptive Statistics

| Item | N | Mean | StDev | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Freq_Topic 1 | 2,207 | 5.121 | 20.447 | 0.000 | 0.003 | 0.007 | 0.017 | 99.940 |
| Freq_Topic 2 | 2,207 | 5.043 | 20.626 | 0.000 | 0.003 | 0.007 | 0.020 | 99.934 |
| Freq_Topic 3 | 2,207 | 2.441 | 13.409 | 0.000 | 0.008 | 0.018 | 0.055 | 99.773 |
| Freq_Topic 4 | 2,207 | 3.968 | 17.793 | 0.000 | 0.004 | 0.012 | 0.036 | 99.901 |
| Freq_Topic 5 | 2,207 | 3.475 | 16.227 | 0.000 | 0.005 | 0.014 | 0.044 | 99.835 |
| Freq_Topic 6 | 2,207 | 4.828 | 19.686 | 0.000 | 0.003 | 0.009 | 0.020 | 99.934 |
| Freq_Topic 7 | 2,207 | 3.715 | 17.584 | 0.000 | 0.004 | 0.010 | 0.025 | 99.894 |
| Freq_Topic 8 | 2,207 | 4.317 | 18.118 | 0.000 | 0.007 | 0.014 | 0.043 | 99.877 |
| Freq_Topic 9 | 2,207 | 4.883 | 20.521 | 0.000 | 0.004 | 0.008 | 0.020 | 99.978 |
| Freq_Topic 10 | 2,207 | 4.813 | 16.571 | 0.000 | 0.011 | 0.024 | 0.116 | 99.870 |
| Freq_Topic 11 | 2,207 | 3.330 | 15.479 | 0.000 | 0.004 | 0.009 | 0.025 | 99.959 |
| Freq_Topic 12 | 2,207 | 6.648 | 23.855 | 0.000 | 0.002 | 0.008 | 0.024 | 99.939 |
| Freq_Topic 13 | 2,207 | 6.406 | 22.932 | 0.000 | 0.004 | 0.009 | 0.028 | 99.932 |
| Freq_Topic 14 | 2,207 | 2.221 | 13.626 | 0.000 | 0.001 | 0.004 | 0.012 | 99.973 |
| Freq_Topic 15 | 2,207 | 5.477 | 21.310 | 0.000 | 0.004 | 0.009 | 0.022 | 99.952 |
| Freq_Topic 16 | 2,207 | 7.566 | 25.358 | 0.000 | 0.003 | 0.008 | 0.019 | 99.939 |
| Freq_Topic 17 | 2,207 | 6.527 | 23.341 | 0.000 | 0.004 | 0.009 | 0.023 | 99.939 |
| Freq_Topic 18 | 2,207 | 7.043 | 23.956 | 0.000 | 0.004 | 0.012 | 0.036 | 99.983 |
| Freq_Topic 19 | 2,207 | 6.913 | 23.799 | 0.000 | 0.003 | 0.009 | 0.025 | 99.975 |
| Freq_Topic 20 | 2,207 | 5.265 | 21.145 | 0.000 | 0.004 | 0.008 | 0.020 | 99.931 |
| Control Variables | | | | | | | | |
| FFO/Share | 1,861 | 1.986 | 4.114 | -18.258 | 0.593 | 1.385 | 2.579 | 127.368 |
| Size | 2,020 | 7.759 | 1.314 | -1.931 | 7.106 | 7.907 | 8.558 | 10.556 |
| Leverage | 2,020 | 0.566 | 0.181 | 0.000 | 0.473 | 0.560 | 0.660 | 1.638 |
| Δ REV | 1,876 | 47.207 | 204.435 | -4,403.782 | 1.039 | 21.619 | 68.020 | 3,701.640 |
| Sales_Growth | 1,862 | 0.034 | 0.436 | -0.800 | 0.001 | 0.011 | 0.027 | 16.478 |
| Beta | 1,892 | 0.974 | 0.495 | -0.692 | 0.622 | 0.927 | 1.259 | 4.661 |
| BTM | 1,956 | -0.116 | 3.018 | -64.892 | -0.049 | 0.0002 | 0.001 | 75.038 |
| IO | 1,749 | 0.760 | 0.283 | 0.000 | 0.637 | 0.838 | 0.954 | 2.383 |
| $Vola^{S\&P}$ (-5, 0 days) | 1,543 | 0.019 | 0.012 | 0.002 | 0.010 | 0.017 | 0.025 | 0.082 |
| $Vola^{S\&P}$ (-40, 0 days) | 1,537 | 0.056 | 0.030 | 0.025 | 0.038 | 0.047 | 0.056 | 0.175 |
| $Vola^{S\&P}$ (-60, 0 days) | 1,535 | 0.068 | 0.031 | 0.030 | 0.052 | 0.056 | 0.078 | 0.193 |
| Δ Volume (0, 5 days) | 1,543 | 0.119 | 0.893 | -4.306 | -0.049 | 0.025 | 0.183 | 20.333 |
| Δ Volume (0, 40 days) | 1,529 | 0.052 | 0.545 | -2.601 | -0.085 | 0.001 | 0.095 | 7.790 |
| Δ Volume (0, 60 days) | 1,519 | 0.050 | 0.520 | -2.860 | -0.082 | 0.003 | 0.100 | 7.646 |
| Text_Length | 2,207 | 68,231 | 50,034 | 36 | 38,302 | 57,270 | 87,198 | 516,463 |
| FOG | 2,207 | 22.460 | 1.707 | 5.000 | 21.665 | 22.496 | 23.307 | 29.698 |
| Dependent Variables | | | | | | | | |
| Vola (0, 5 days) | 1,543 | 0.041 | 0.047 | 0.001 | 0.020 | 0.032 | 0.047 | 1.125 |
| Vola (0, 40 days) | 1,537 | 0.116 | 0.123 | 0.030 | 0.071 | 0.085 | 0.110 | 2.119 |
| Vola (0, 60 days) | 1,535 | 0.142 | 0.132 | 0.033 | 0.088 | 0.107 | 0.141 | 2.130 |

This table shows the descriptive statistics for the frequencies (in %) for the risk factor topics (Freq_Topic) of Item 1A, further control variables, and dependent variables (Vola). The definition of all variables is presented in Table A.3 in Appendix A. N is the number of observations, StdDev stands for standard deviation, Q1 is the first and Q3 the third quartile of the distribution, and Min is the minimum and Max the maximum of each variable. N is set to the maximal available number of observations for each variable.

by 17. What is surprising is the low minimum with 5.0, probably induced by the short reports mentioned above, since the value 10 is only at the level of a high school sophomore (usually aged 15-16).

## 5.5 Results

### 5.5.1 Topic Models and Investor Risk Perception

To test whether the probabilities of risk topics help to explain investor risk perception (Hypothesis 1) in Table 5.2, we regress those probabilities on the stock return volatility. We run three model specifications, for which we alternate the dependent variable (Vola) according to the time horizon of investor risk perception – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3) after the respective 10-K filing was published.

After controlling for firm-level characteristics and other textual measures that have been shown to be associated with volatility in previous studies, we find that the STM extracted risk factors help to explain investor risk perceptions for all three model specifications. The relevance of risk factors is statistically more pronounced in the short run (Model 1), encompassing 12 out of 16 topics, compared to the long run (Models 2 and 3), where the count decreases to 6 and 7 topics, respectively. Beyond the numerical shift, the magnitudes of risk factor coefficients decrease across the three time horizons of investor risk perception (Models 1-3), with the exception of Topic #1 "Transaction" and Topic #15 "Single Tenant Risk". The diminishing effects of coefficients over time, transitioning from significant to insignificant, align with the efficient market hypothesis, suggesting that the impact of new information diminishes as time progresses. The signs of coefficients remain consistent across horizons, barring Topic #15 "Single Tenant Risk", indicating a robust association between the risk topics and return volatility. While the number of significant controls remains constant across the three time horizons, their magnitudes exhibit mostly an increase in the long run. Once again, this aligns with the efficient market hypothesis, implying that firm fundamentals gain greater impact over time.

The results for the other topic model approaches (LDA and CTM) have similar results for the fundamentals (significance and magnitude). However, the majority of whose risk topics are insignificant which is in line with Bao and Datta (2014). We compare all approaches in more detail in Subsection 5.6 and use STM for the next analyses since it is more efficient to extract topics explaining the investors' risk perception.

Some fundamentals are never relevant (FFO/Share, ΔREV, and Sales_Growth), others increase their impact over the time horizons and mitigate the impact of risk factors. Leverage is the only fundamental variable that is significant in the short-run, but insignificant in the long run. This is not surprising since Beta already incorporates a large part of the risk. The ratio of institutional owners (IO), volatility of the last trading days (Lag_Vola), and trading volume (ΔVolume) also increase their impact over the models with a longer time window. The two alternative textual variables (Text_Length and FOG) are never relevant

Table 5.2: Probability of Appearance – Risk Perception

| | Model 1 (0, 5 days) | Model 2 (0, 40 days) | Model 3 (0, 60 days) |
|---|---|---|---|
| Freq_Topic 1 | -0.006*** | -0.015*** | -0.014*** |
| | (0.002) | (0.005) | (0.005) |
| Freq_Topic 2 | 0.031*** | 0.028*** | 0.030*** |
| | (0.003) | (0.007) | (0.007) |
| Freq_Topic 3 | -0.011*** | -0.004 | -0.006 |
| | (0.002) | (0.004) | (0.004) |
| Freq_Topic 4 | 0.039*** | 0.028*** | 0.031*** |
| | (0.003) | (0.007) | (0.007) |
| Freq_Topic 5 | 0.009*** | 0.008* | 0.008 |
| | (0.002) | (0.005) | (0.005) |
| Freq_Topic 6 | -0.0003 | -0.008* | -0.009** |
| | (0.002) | (0.005) | (0.004) |
| Freq_Topic 8 | -0.010*** | -0.005 | -0.008** |
| | (0.002) | (0.003) | (0.003) |
| Freq_Topic 9 | 0.002 | -0.004 | -0.004 |
| | (0.002) | (0.004) | (0.004) |
| Freq_Topic 10 | -0.003*** | 0.001 | 0.001 |
| | (0.001) | (0.002) | (0.002) |
| Freq_Topic 12 | 0.0001 | -0.005 | -0.004 |
| | (0.001) | (0.003) | (0.003) |
| Freq_Topic 13 | -0.017*** | -0.008 | -0.010** |
| | (0.002) | (0.005) | (0.005) |
| Freq_Topic 15 | -0.013*** | 0.009** | 0.010** |
| | (0.002) | (0.004) | (0.004) |
| Freq_Topic 16 | -0.007*** | -0.003 | -0.005 |
| | (0.002) | (0.004) | (0.004) |
| Freq_Topic 17 | -0.004** | -0.004 | -0.004 |
| | (0.002) | (0.004) | (0.004) |
| Freq_Topic 19 | -0.013*** | -0.005 | -0.006 |
| | (0.002) | (0.005) | (0.005) |
| Freq_Topic 20 | 0.003 | 0.002 | 0.003 |
| | (0.002) | (0.004) | (0.004) |
| FFO/Share | 0.0005 | 0.002 | 0.001 |
| | (0.001) | (0.002) | (0.002) |
| Size | 0.002 | 0.013* | 0.014* |
| | (0.003) | (0.007) | (0.007) |
| Leverage | 0.025** | 0.016 | 0.006 |
| | (0.013) | (0.028) | (0.027) |
| Δ REV | 0.00000 | -0.00001 | -0.00002 |
| | (0.00001) | (0.00002) | (0.00002) |
| Sales_Growth | 0.005 | -0.004 | -0.004 |
| | (0.004) | (0.009) | (0.009) |
| Beta | 0.009*** | 0.024*** | 0.013* |
| | (0.003) | (0.008) | (0.008) |
| BTM | -0.020*** | 0.056*** | 0.066*** |
| | (0.002) | (0.006) | (0.006) |
| IO | -0.018*** | -0.043*** | -0.036*** |
| | (0.006) | (0.013) | (0.013) |
| Lag_Vola | 0.350*** | 0.352*** | 0.542*** |
| | (0.038) | (0.062) | (0.045) |
| $Vola^{S\&P}$ | 0.168 | 0.079 | 0.316 |
| | (0.123) | (0.231) | (0.212) |
| Δ Volume | 0.008*** | 0.022*** | 0.022*** |
| | (0.002) | (0.004) | (0.004) |
| Text_Length | -0.005 | 0.014 | 0.011 |
| | (0.004) | (0.010) | (0.009) |
| FOG | -0.0001 | -0.0003 | -0.0003 |
| | (0.002) | (0.004) | (0.004) |
| VIF Min | 1.065 | 1.099 | 1.065 |
| VIF Max | 3.724 | 4.801 | 5.703 |
| N | 1,228 | 1,224 | 1,223 |
| $R^2$ | 0.318 | 0.182 | 0.272 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 1A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3). The definition of all variables is presented in Table A.3 in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

so that the risk factors convey the information. Consequently, the alternatives are not very suitable as viable alternatives for the risk topics.

We examine multicollinearity among all control and topic variables by employing the Variance Inflation Factor (VIF) in our models. The minimal and maximal VIF values (VIF Min and VIF Max) are reported in Table 5.2. Notably, all topic probabilities exhibit a VIF below 5, as we exclude topics with elevated VIF values in a preliminary step. Among the control variables, only the volatility of the S&P 500 surpasses a VIF of 5, specifically in the longest time horizon (Model 3). The goodness of fit ($R^2$) decreases from Model 1 to Models 2 and 3 (32% vs. 18% and 27%) due to the lower importance of the risk factors but improves from Models 2 and 3. This latter effect is mostly driven by the higher importance of few controls (IO, Beta, and Lag_Vola) in the long run.

### 5.5.2 Baseline Models without Risk Topics

In order to better assess the extent to which the probabilities of risk topics have an impact on volatility, we repeat the previous analysis without the topic probabilities (baseline models).

Most of the control variables (10 of 13) show a similar influence on the stock return volatility in the baseline models compared to the previous analysis. They are either insignificant or significant to a comparable magnitude. Among the variables that behave differently are Size (significant in Models 2 and 3 in baseline models) and Leverage (significant in Model 1 in baseline models). The third variable, which behaves differently, deserves a closer look. In the baseline models, the volatility of the market index ($Vola^{S\&P}$) is significantly positive for all three time windows (Models 1-3) but not if we include the topic probabilities (Table 2). In addition, the two alternative textual variables (Text_Length and FOG) are still not significant so these cannot be used as alternatives for our developed risk topic probabilities. The last two results in particular show that our method used in Table 5.3 helps to disentangle a simple linear relationship between market-wide risk ($Vola^{S\&P}$) and a firm's volatility into specific risk topic-related relationships.

Based on a comparison of the adjusted $R^2$ between the models of Table 5.2 and Table 5.3, we confirm the previous findings: the risk factors are statistically more relevant in the short-run (Model 1) than in the long run (Model 3). After adding topic probabilities, the adjusted $R^2$ increases by 51% in Model 1 (0.301 vs. 0.200), decreases by 4% in Model 2 (0.162 vs. 0.166), and increases by 6% in Model 3 (0.254 vs. 0.241).

Table 5.3: Baseline Models

| | **Model 1** (0, 5 days) | **Model 2** (0, 40 days) | **Model 3** (0, 60 days) |
|---|---|---|---|
| FFO/Share | -0.00004 | 0.001 | 0.001 |
| | (0.001) | (0.002) | (0.002) |
| Size | 0.0005 | 0.006 | 0.006 |
| | (0.003) | (0.007) | (0.007) |
| Leverage | 0.018 | 0.003 | -0.008 |
| | (0.013) | (0.027) | (0.026) |
| ΔREV | 0.00000 | -0.00002 | -0.00002 |
| | (0.00001) | (0.00002) | (0.00002) |
| Sales_Growth | 0.004 | -0.001 | -0.003 |
| | (0.004) | (0.009) | (0.009) |
| Beta | 0.010*** | 0.027*** | 0.019** |
| | (0.003) | (0.007) | (0.007) |
| BTM | -0.019*** | 0.055*** | 0.065*** |
| | (0.002) | (0.006) | (0.006) |
| IO | -0.019*** | -0.044*** | -0.038*** |
| | (0.006) | (0.013) | (0.013) |
| Lag_Vola | 0.316*** | 0.308*** | 0.499*** |
| | (0.040) | (0.058) | (0.043) |
| VolaS&P | 0.895*** | 1.592*** | 1.300*** |
| | (0.144) | (0.293) | (0.309) |
| ΔVolume | 0.006*** | 0.020*** | 0.020*** |
| | (0.002) | (0.004) | (0.004) |
| Text_Length | -0.001 | 0.010 | 0.006 |
| | (0.004) | (0.009) | (0.009) |
| FOG | 0.001 | 0.002 | 0.003 |
| | (0.002) | (0.004) | (0.004) |
| VIF Min | 1.065 | 1.099 | 1.065 |
| VIF Max | 3.724 | 4.801 | 5.703 |
| N | 1,228 | 1,224 | 1,223 |
| $R^2$ | 0.208 | 0.175 | 0.249 |

This table presents baseline models for the results of Table 2; we excluded the probabilities of risk topics but all other specifications are the same as in Table 2. This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 7A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3). The definition of all variables is presented in Table A.3 in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

### 5.5.3 Risk Disclosures resolve Uncertainties

To test Hypothesis 2, which predicts a risk-reducing effect for the majority of risk factors, we evaluate the coefficient signs of the extracted risk factors. Consistent with Bao and Datta (2014), our results provide support for all three influencing effects. Contrary to those who find that the majority of their LDA-extracted risk factors carry no relevant information for the market, the majority of our STM-extracted risk factors reduce significantly the volatility and follow therefore the convergence argument.

In Model 1 (5-day window), four risk factor topics #6, #9, #12, and #20,[6] have an insignificant coefficient, supporting the null argument of an uninformative risk factor. Three risk factors, including topics #2, #4, and #5 are positively associated with stock

[6]We describe the topic labels in the next subsection.

return volatility (divergence argument). The convergence factors are in the majority (topics #1, #3, #8, #10, #13, #15, #16, #17, and #19), which is in line with the assumption that firms use 10-Ks to resolve known risk factors or give more facts about known risk factors and thus, reduce risk perceptions among investors. These values are economically significant, too. For example, the standardized beta of topics #1, #3, and #13; if we increase the risk topic by one standard deviation, the volatility decreases by -17%, -24%, and -53% of its standard deviation. The economic impact for the divergence topics is on average greater with 91%, 107%, and 23%. Overall and on average, the risk topics' impact is on the same scale as those of the traditional fundamental variables (e.g., Size 6%, Lag_Vola 37%, or BTM -137%). The results for the longer time windows (Models 2 and 3) are the same as discussed in the previous subsection: the risk factors are more relevant in the short-run (Model 1) than in the long run (Models 2 and 3) and most fundamentals increase their impact in the long run.

Based on the statistical and economic significance of the convergence factors, we conclude that executives use this type of disclosure (Item 1A in 10-K) mainly to resolve risk instead of presenting new risk factors so that risk disclosures may even be seen as 'good news' as long as they clarify the impact of already known factors. This is in line with the majority of the previous literature of a volatility reducing effect of risk disclosures even if they are not or only to a limited extent able to explain why this happens (e.g., Huang and Li, 2011). Common to most of the so-far used measures (e.g., text length or number of keywords) is that they do not allow a deeper look (i.e. semantic) into the risk-reducing drivers of their – mostly – single risk factor model. Our proposed solution instead allows to combine risk increasing and reducing effects in a single model.

### 5.5.4 Semantic and Economic Interpretation

Topic modeling has the advantage that it delivers more risk factors with a higher granularity which can be interpreted economically (e.g., Bao and Datta, 2014). For example, STM does not only provides frequencies of appearance, but also the corresponding set of words representing the topic. Our results indicate, that risk factors talking about Tax and Capital Contribution, Acquisition, IT, and Property (#6, #9, #12, and #20) have no effect on stock return volatility after the filing submission date (see Model 1 of Table 2). The risk factor topics supporting the divergence argument comprise Regulation, Unsecured Claims and Debts, and Rating (#2, #4, and #5). The convergence factors cover the topics Transaction, Business Process, Capital Products and Market, Contingencies, Legal & Litigation Risk, Single Tenant Risk, Property, Politics, and Cash-flow (#1, #3, #8, #10, #13, #15, #16, #17, and #19).

However, these topic labels give only a first insight. Topic modeling provides the set of words (e.g., top 20) representing the risk factor while researchers choose the label. Therefore, labels may not describe topics entirely. Israelsen (2014) gets to the heart of this dilemma by stating that "it is the words that define the topics, not the title". For example, the convergence factor #1 "Transaction" includes words such as 'unenforceable', 'origination', 'repurchases', and 'sale-leaseback'. The frequent appearance of phrases such as 'plaintiffs', 'defendant', 'supreme', and 'prejudice' suggests that the corresponding topic #13 is related to "Legal & Litigation risk". For other topics, however, it is more difficult to find a one-title-fits-all label. For example, topic #10 of contains phrases such as 'hackers', 'terrorists', 'libor', and 'tcja' (Tax Cuts and Jobs Act), and thus, the interpretation is somewhat blurry or mixed. In this case, examining disclosures including these keywords can be helpful in finding the missing link among the STM-identified words for a topic, being able to find a generic topic and interpret its meaning. The annual report of Boston Properties, Inc. in 2018 discusses certain 'risks associated with security breaches through cyber attacks', 'terrorist attacks may adversely affect the ability to generate revenues', and 'tax changes that could negatively impact financials' in close proximity to each other. A deeper look into the documents shows that numerous disclosures raise these risks directly one after the other. Given that topic models rely on word co-occurrences and ignore visual clues (e.g., subsection titles, boldface fonts, extra spacing) or logical coherence, the resulting "mixture of topics" is the consequence. At a higher level, however, topic #10 can be subsumed as "Contingencies".

Similarly, polysemy – the capacity for a word to have multiple meanings – makes it harder to label topics. At first glance, the words 'migration' and 'recycling' do not fit with the other words in the divergence topic #5 (e.g., 'moodys', 'poors') which intuitively entails the label "Rating". However, the word 'migration' may also be used in the context of 'rating migration' and 'recycling' might refer to 'capital recycling' which may be the reason for a rating upgrade or downgrade.

### 5.5.5 Probability of Appearance vs. Absolute Allocation of Words

So far, our analyses focus on the probability of appearance of risk factor topics and ignore the number of words a firm allocates towards a specific risk. For example, even in the extreme case that a firm describes litigation risk with 100% within its 10-word long risk disclosure, it seems that this risk is for this firm much less material than for another firm that allocates 20% of its 1000-word long disclosure towards litigation risk. We adapt our target variables by multiplying the probability of appearance for each risk factor (Freq_Topics) with the total length of the corresponding disclosure (Text_Length). This approach presents a hybrid model using machine learning and widely used word-count methods. We regress the log transformation of the new target variable (Abs_Allocation) on the stock return volatility following the 5, 40, and 60 trading-day windows. The descriptive statistics of Abs_Allocation are given in Table 5.4 and the results of the regression model which follows Equation (3) are in Table 5.5.

Table 5.4: Descriptive Statistics – Absolute Allocation of Words

| | N | Mean | StDev | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Item 1A | | | | | | | | |
| *Abs_Allocation* 1 | 2,157 | 4,784.894 | 20,770.350 | 0.025 | 1.368 | 3.466 | 9.380 | 211,302.900 |
| *Abs_Allocation*2 | 2,157 | 3,180.996 | 14,577.500 | 0.001 | 1.536 | 3.854 | 11.476 | 138,226.600 |
| *Abs_Allocation* 3 | 2,157 | 899.028 | 6,324.319 | 0.106 | 4.675 | 10.062 | 28.268 | 133,751.700 |
| *Abs_Allocation* 4 | 2,157 | 2,200.952 | 11,153.190 | 0.003 | 2.174 | 6.535 | 21.225 | 108,071.900 |
| *Abs_Allocation* 5 | 2,157 | 1,680.289 | 8,918.072 | 0.104 | 3.044 | 7.509 | 21.734 | 142,100.100 |
| *Abs_Allocation* 6 | 2,157 | 4,300.814 | 20,565.220 | 0.053 | 1.514 | 4.321 | 11.861 | 175,507.700 |
| *Abs_Allocation* 7 | 2,157 | 2,074.562 | 10,261.370 | 0.001 | 2.203 | 5.334 | 14.812 | 97,628.020 |
| *Abs_Allocation* 8 | 2,157 | 2,005.718 | 8,796.460 | 0.207 | 4.073 | 8.368 | 21.142 | 87,897.500 |
| *Abs_Allocation* 9 | 2,157 | 4,258.056 | 23,163.760 | 0.057 | 1.985 | 4.361 | 9.766 | 358,091.100 |
| *Abs_Allocation* 10 | 2,157 | 2,517.047 | 8,149.857 | 0.156 | 6.277 | 12.305 | 48.238 | 72,535.240 |
| *Abs_Allocation* 11 | 2,157 | 2,618.542 | 13,752.160 | 0.001 | 1.997 | 5.100 | 15.108 | 186,137.400 |
| *Abs_Allocation* 12 | 2,157 | 3,524.577 | 14,625.800 | 0.0001 | 1.418 | 4.120 | 12.151 | 132,529.400 |
| *Abs_Allocation* 13 | 2,157 | 4,080.354 | 16,148.920 | 0.001 | 1.704 | 4.595 | 14.166 | 173,824.100 |
| *Abs_Allocation* 14 | 2,157 | 2,124.229 | 14,972.500 | 0.001 | 0.593 | 2.183 | 6.113 | 180,428.300 |
| *Abs_Allocation* 15 | 2,157 | 4,613.534 | 20,843.580 | 0.023 | 2.390 | 5.010 | 12.168 | 241,480.400 |
| *Abs_Allocation* 16 | 2,157 | 4,252.121 | 16,687.200 | 0.071 | 1.798 | 4.441 | 11.206 | 159,719.300 |
| *Abs_Allocation* 17 | 2,157 | 4,191.365 | 16,482.040 | 0.161 | 2.496 | 4.602 | 12.725 | 126,125.000 |
| *Abs_Allocation* 18 | 2,157 | 4,892.229 | 26,515.550 | 0.001 | 2.442 | 7.021 | 20.794 | 516,358.900 |
| *Abs_Allocation* 19 | 2,157 | 6,162.992 | 31,754.840 | 0.041 | 1.925 | 4.782 | 12.686 | 410,365.500 |
| *Abs_Allocation* 20 | 2,157 | 3,981.453 | 17,581.560 | 0.138 | 2.208 | 4.583 | 10.895 | 137,661.800 |

This table shows the descriptive statistics for the frequencies (in %) for the risk factor topics multiplied by the total length of the corresponding disclosure (Abs_Allocation). N is the number of observations, StdDev stands for standard deviation, Q1 is the first and Q3 the third quartile of the distribution, and Min is the minimum and Max the maximum of each variable. N is set to the maximal available number of observations for each variable.

Consistent with previous findings 12 of 16 risk topics are significantly associated with volatility in the short-run (5-day window). Again, the risk factor influence varies over the windows. Comparable to the probability model (Subsection 5.5.1), we observe lower significant coefficients for the risk factors if we move to 40 trading days (8 risk factors instead of 7) or to 60 trading days (8 risk factors instead of 7). Considering the rising impact of most of the control variables, this observation further aligns with the efficient market hypothesis. It implies that as time progresses, the diminishing effect of new information occurs concurrently with an increasing effect of fundamental factors.

As in the earlier probability model, multicollinearity is not a concern for the independent variables. In comparison to the probability model, the absolute allocation of words model explains the variations better; the $R^2$ is on average 2 percentage points greater for all windows. For example, the model with Abs_Allocation explains around 35% of the variation for the 5-day window, whereas Freq_Topics explains 32%. The goodness of fit decreases for longer windows – 21% for 40 days and 28% for 60 days – but remains higher than all models using Freq_Topics.

Based on the comparable coefficients and the higher explanatory power for the Abs_Allocation model, we evaluate this hybrid model as a good instance to combine machine learning with a classical factor. Thereby, a combination of the number of words

Table 5.5: Absolute Allocation of Words – Risk Perception

| | Model 1 (0, 5 days) | Model 2 (0, 40 days) | Model 3 (0, 60 days) |
|---|---|---|---|
| Abs_Allocation 1 | -0.007*** | -0.016*** | -0.015*** |
| *Transaction* | (0.002) | (0.005) | (0.005) |
| Abs_Allocation 2 | 0.032*** | 0.027*** | 0.030*** |
| *Regulation* | (0.003) | (0.007) | (0.007) |
| Abs_Allocation 3 | -0.011*** | -0.005 | -0.006 |
| *Business Process* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 4 | 0.038*** | 0.029*** | 0.031*** |
| *Unsecured Claims and Debts* | (0.003) | (0.007) | (0.007) |
| Abs_Allocation 5 | 0.009*** | 0.010** | 0.008* |
| *Rating* | (0.002) | (0.005) | (0.005) |
| Abs_Allocation 6 | -0.001 | -0.009** | -0.009** |
| *Tax and Capital Contribution* | (0.002) | (0.005) | (0.004) |
| Abs_Allocation 8 | -0.010*** | -0.006 | -0.008** |
| *Capital Products and Market* | (0.002) | (0.003) | (0.003) |
| Abs_Allocation 9 | 0.002 | -0.004 | -0.004 |
| *Acquisition* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 10 | -0.002*** | 0.001 | 0.001 |
| *Contingencies* | (0.001) | (0.002) | (0.002) |
| Abs_Allocation 12 | 0.00001 | -0.005* | -0.004 |
| *IT* | (0.001) | (0.003) | (0.003) |
| Abs_Allocation 13 | -0.017*** | -0.008* | -0.010** |
| *Legal & Litigation Risk* | (0.002) | (0.005) | (0.005) |
| Abs_Allocation 15 | -0.012*** | 0.009* | 0.010** |
| *Single Tenant Risk* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 16 | -0.007*** | -0.002 | -0.005 |
| *Property* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 17 | -0.005*** | -0.004 | -0.004 |
| *Politics* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 19 | -0.012*** | -0.005 | -0.006 |
| *Cash-flow* | (0.002) | (0.005) | (0.005) |
| Abs_Allocation 20 | 0.003 | 0.003 | 0.004 |
| *Property* | (0.002) | (0.004) | (0.004) |
| FFO/Share | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.002) | (0.002) |
| Size | 0.001 | 0.012* | 0.013* |
| | (0.003) | (0.007) | (0.007) |
| Leverage | 0.029** | 0.018 | 0.007 |
| | (0.012) | (0.028) | (0.027) |
| $\Delta$ REV | 0.00000 | -0.00001 | -0.00002 |
| | (0.00001) | (0.00002) | (0.00002) |
| Sales_Growth | 0.005 | -0.004 | -0.006 |
| | (0.004) | (0.009) | (0.009) |
| Beta | 0.009*** | 0.024*** | 0.015** |
| | (0.003) | (0.007) | (0.007) |
| BTM | -0.020*** | 0.056*** | 0.066*** |
| | (0.002) | (0.006) | (0.006) |
| IO | -0.018*** | -0.044*** | -0.038*** |
| | (0.006) | (0.013) | (0.013) |
| Lag_Vola | 0.354*** | 0.328*** | 0.521*** |
| | (0.037) | (0.058) | (0.043) |
| $Vola^{S\&P}$ | 0.866*** | 1.610*** | 1.290*** |
| | (0.133) | (0.291) | (0.305) |
| $\Delta$ Volume | 0.007*** | 0.020*** | 0.020*** |
| | (0.002) | (0.004) | (0.004) |
| Text_Length | -0.005 | 0.002 | -0.001 |
| | (0.005) | (0.010) | (0.010) |
| FOG | -0.0003 | -0.00005 | 0.00004 |
| | (0.002) | (0.004) | (0.004) |
| VIF Min | 1.065 | 1.062 | 1.065 |
| VIF Max | 3.724 | 4.801 | 5.703 |
| N | 1,228 | 1,224 | 1,223 |
| $R^2$ | 0.345 | 0.207 | 0.283 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 1A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3). The definition of all variables is presented in Table A.3 in Appendix A. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and machine-assisted topic modeling helps to explain investor risk perceptions most efficiently. The topics are most important for a short window even after controlling for traditional firm-specific accounting and market control variables.

### 5.5.6 Alternative of Risk Perception and Alternative Topic Models

To examine the robustness of our finding that the majority of the risk factors follow the convergence argument, we alter the measure of risk perception and topic modeling approach. For the alternative measure of risk, we follow Kravet and Muslu (2013) and re-run our analysis using the change in the standard deviation of a firm's daily stock returns from the symmetric period of T trading-days before to after the 10-K is filed. This measure also controls for serial correlation issues for the dependent variable. They calculate the difference between the volatility during the first 60 trading days after the filings and the last 60 trading days before the filings. Higher volatility after the filing goes in line with the divergence argument whereas lower volatility is supported by the convergence argument. Our results are robust to this alternated dependent variable since all coefficients' signs are the same and their magnitudes have a comparable size (see Table A.6 in Appendix A). Thus, our conclusion that most risk factors follow the convergence argument applies even after using a different measure of risk perception, too.

After presenting an alternative for the dependent side, we change the topic extracting process on the independent side, too. Even if Blei and Lafferty (2007) and Roberts et al. (2014) show that STM and CTM are superior to LDA, we want to stress our results and use all three topic model approaches for our best model (Abs_Allocation). Within this robustness check, we additionally run regressions for CTM and LDA extracted risk factor topics over the 5 trading-day and 60 trading-day periods and compare them with STM. Note that the model-specific topics are not directly comparable since their words are different. In the short-run, LDA identifies three risk factors and CTM four risk factors that are significantly associated with investor risk perception; these numbers are lower than the twelve factors for STM. STM also leads in the long run with eight significant risk factors, CTM has no significant factor and LDA two factors. This relatively low number could also be induced by randomness around the t-value and not from the economic significance of the factors. Additionally, the goodness of fit is highest for STM for both time windows. Thus, we conclude that our empirical findings confirm the theoretical and empirical derived superiority of STM within the economic field (see Subsection 5.3.1) as the advanced approach. The results are presented in Table A.8 in Appendix A.

### 5.5.7 Validity of the STM to capture Changes in Reporting Behavior

The lessons of the subprime crises (2007-2009) and the strengthened disclosure requirements of the SEC changed the reporting behavior of companies. To further assess the validity of our method, we analyze whether the STM identified probabilities of appearance are capable of capturing these changes in 10-Ks. To conduct the analysis, we calculate the yearly growth rate of the probability of appearance for each of the risk factors over all firms. Figure 5.6 illustrates these growth rates for selected topics whose reporting certainly changed during or after the crisis: Regulation (#2), Rating (#5), and Single Tenant Risk (#15).

Figure 5.6: Yearly Growth Rate of the Probability of Appearance


This figure shows yearly growth rates of the probability of appearance for the topics Regulation (#2), Single Tenant Risk (#15), and Rating (#5).

We observe that topic #2 Regulation had decreased before/during the crisis and increased in the aftermath, representing strengthened regulatory requirements after the crisis. Contrary, Single Tenant Risk (#15) peaked in 2009 and 2011 and has increased on average in the aftermath of the subprime crisis. This might be due to strengthened disclosure requirements, or it showcases that risk factors become immanent or even real threats for the company during an economic crisis. Rating (#5) dropped in the year 2010 and has oscillated since then around zero. This trend may reflect the loss of confidence in rating agencies following the events of 2007 and 2008. In summary, probabilities of appearance are time-varying and deviate from their previous level when specific events (e.g., subprime crisis) occur. Thus, disclosure frequencies reflect changes in firms' reporting behavior caused by specific events, confirming the validity of the STM.

### 5.5.8 Generalization of the Results with another Dataset

In order to test the theoretical-motivated findings that STM is superior in comparison to CTM and LDA in analyzing risk, we repeat the major empirical analyses of Subsection 5.5.1. and 5.5.6. to a new dataset – mortgage REITs and unclassified REITs. Mortgage REITs, unlike equity REITs, exhibit less homogeneity, a diminished perception among investors, and lower quality and standardization in risk reporting. Our findings for this new sample support our previous findings. Notably, the STM algorithm yields more meaningful and statistically significant topics explaining the return's volatilities compared to the other two algorithms (CTM and LDA). The risk factor's coefficients are mostly negative supporting the risk reduction argument through corporate disclosures (convergence argument). The coefficient's magnitudes reduce over the horizon (Model 1 to Model 3). Most of the controls are insignificant or have a higher influence in the long run. These findings align with the efficient market hypothesis, suggesting that the impact of new information (risk topics) diminishes and the impact of fundamentals increases as time progresses. The two alternative textual variables (Text_Length and FOG) are never significant so the STM-derived risk topics convey the information. Consequently, these alternatives are not suitable as viable alternatives for the risk topics. The goodness of fit ($R^2$) decreases from STM to CTM and to LDA supporting that STM-based risk factors are most suitable to explain the return volatility. The descriptive statistics of the new variables and the regression results are presented in Table D.1 and D.2 in Appendix D.

Considering the unfavorable market condition in this new dataset, we have reasons to conclude that our results can be generalized and the unsupervised machine-learning algorithm incorporating metadata of pre-specified covariates (STM) produces more meaningful and statistically significant topics influencing volatility compared to the other two ML algorithms or straightforward risk factors.

## 5.6 Conclusion

Firms have to inform their shareholders about the expected implications and consequences of adverse events so that the investors are able to monitor the current and future risk factors a firm is facing and integrate them into their decision-making analysis. Specifically, the SEC mandates firms to discuss the most relevant factors that may entail speculative or risky aspects for the firm in their 10-Ks. Recognizing the temporal and cognitive limitation of human investors to read and react to the massive amount of text, we exploit unsupervised machine learning approaches (STM, CTM, and LDA), allowing the user to identify and quantify the risk factors discussed in REITs' 10-Ks. However, since the so-far most used LDA is limited when identifying common risk factors across industries or sectors, we extend the applied toolbox with the advanced topic modeling approaches (STM and CTM) and are the first who apply these techniques in the accounting and finance domain. We are able to confirm the theoretical and previously shown superiority of STM over CTM and LDA in an economic application. To assess whether our machine-assisted topic modeling presents a valid approach to quantify risk in narrative form, we analyze whether the STM extracted risk factors help to explain the perceived risk on the stock market in general. In a first step, we observe that models incorporating topic probabilities contribute to a more detailed understanding of how a firm's volatility can be explained, particularly in the short term. Simple straight-forwarded proxies of textual variables (e.g., word count, text length) are not viable alternatives for topic-modeling derived risk topics. In the next step, we find that the majority of risk topics are significantly associated with volatility, confirming the effectiveness of our model in comparison to LDA-focused studies which find for example mostly insignificant results (Bao and Datta, 2014). Furthermore, we allow our fine-grained risk topics to carry all three types of risk perception (null argument, divergence argument, and convergence argument, see Kravet and Muslu, 2013). This helps us to resolve contradicting results in the literature by our way of addressing a problem. We find evidence supporting all three types of price reactions to information. Four risk factors support the null argument of uninformative disclosures, three risk factors reveal previously unknown contingencies to investors, thus increasing their risk perceptions (divergence argument), and the majority (nine risk factors) decrease risk perceptions (convergence argument). We repeat our primary analyses using new data under unfavorable market conditions to generalize our outcomes. The results from the new data also substantiate our key findings. The predominance of risk-reducing risk factors is in line with the majority of the previous literature using more straight-forwarded measures. In addition to previously used method of measuring qualitative textual information by counting words, we can combine this idea of an impact by quantity with our measure of probability. This hybrid model – combining machine learning with the word-counting factor – confirms our previous finding and explains best the variations within our dataset. This achieved finding would not be possible by the so-far mostly used approaches. Thus, we conclude that a combination of the classical word count and our machine-assisted topic modeling helps to explain investor risk perceptions most efficiently. This is our contribution from the technical part. From the practical part, we contribute the finding that Item 1A in the 10-K filings primarily provides essential information on risk factors resolving uncertainties instead of disclosing new risk factors. Consequently, it seems like executives' concerns of adverse effects of disclosing "negative" information are baseless and risks described in 10-Ks can indeed be considered 'good news' as long as executives clarify the implications of already known risk. Our findings support the pursuit to reduce information asymmetry by regulators (e.g., SEC) since both firms and shareholders benefit from reduced volatility showing that markets efficiently incorporate information into prices. In addition, our idea combining machine learning/topic modeling with a classical and straight-forwarded word-counting method as well as state-of-the-art econometric models may help to pave the way for more applications of natural language processing since previous methods were not able to give a deeper understanding of whether and which risk topics influence investors' risk perception.

# Appendix A

## Metadata Covariates for STM

To apply STM to the textual corpus, we include the property type of the respective REIT as metadata covariate. We, therefore, assign the property type as classified by CRSP Ziman to each filing. The metadata covariate "Retail" is, for example, accompanied by the words 'shopping', 'goods', 'e-commerce', 'consumer', 'malls', and 'anchor'. The words 'hotels', 'leisure', 'travelers', 'room', and 'franchise' are instead typically associated with the lodging industry. Observations assigned to the category 'Unknown', meaning that the firm is not assigned to a type for this year in the Ziman dataset are aggregated from the analysis. The group 'Unclassified' includes asset classes like Timber, Data Centers, Infrastructure, and Specialty. These STM-derived word sets for each metadata covariate describe the specifics of each asset class impressively well. Table A.2 in Appendix A shows the full list of metadata covariates, along with their covariate words.

Contrary, topics identified by LDA highly correspond to the investment types (see Table B.1 in Appendix B). For example, LDA Topic #1 corresponds to "Health Care", LDA Topic #4 to "Residential", and LDA Topic #9 to "Retail" to name a few (see discussion in the Introduction for healthcare vs. residential and Table B.1 in Appendix B). Moreover, the frequency of appearance for the individual risk topics identified by LDA is closely related to Ziman property types. Specifically, we find that disclosure frequencies are mostly driven by 1-3 property types (see Table B.2 in Appendix B).

A.2 Metadata Covariates

| Property Type | # of 10-Ks | Covariate Words |
|---|---|---|
| Unknown | 0 | n.a. |
| Unclassified | 264 | generation, equipment, products, pressures, distributing, diversification, appeal, option, letter, planning, finding, uncertain, paying, lesser, oil, larger, capacity, negotiate, satisfying, advantage |
| Diversified | 233 | incident, five-year, weaknesses, raised, rating, diluted, accept, vacancies, renewal, valuation, expiring, dealer, tenant, existence, designed, assumptions, terminated, accounting, grade, insolvent |
| Health Care | 215 | referral, licensure, patients, false, physician, payors, abuse, healthcare, whistleblower, medicare, egate, denial, hospitals, patient, payor, physicians, hipaa, referrals, care, anti-kickback |
| Industrial/ Office | 424 | feet, office, square, egateo, evaluation, undisclosed, downgraded, space, units, evict, budgeted, utilities, perceived, enforcing, building, lack, honor, disclosure, geopolitical, settle |
| Lodging/ Resorts | 269 | brands, hotels, centralized, leisure, travelers, room, revpar, hotel, rooms, building, franchisors, guests, true, adr, reservation, travel, franchise, alerts, respected, lodging |
| Residential | 277 | mae, fannie, residents, homes, mac, egate, apartment, housing, multifamily, fhaa, household, communities, explore, apartments, home, lawsuits, offers, conservatorship, already, regulating |
| Retail | 455 | retailers, shopping, retailing, shoppers, goods, retail, e-commerce, consumer, locations, malls, creditworthiness, traffic, vacated, anchor, tanks, stores, premises, convenience, spaces, approvals |
| Self Storage | 78 | self-storage, extensively, cyber-attack, penetrate, armed, telephone, destructive, avail, commerce, storage, collecting, shutdowns, changed, disruptive, releases, audits, view, worms, protections, integrating |

This table shows the metadata Covariate Words based on 8 of the Ziman Property Types and the number of occurrence within our sample (# of 10-Ks). The STM identifies these covariate words that the algorithm uses to determine the covariate group deviation $K_{y_d}$ and the covariate-topic interactions $K_{y_d,k}$ (see Section 3.2).

A.3: Description of Variables

| | |
|---|---|
| **Dependent Variables** | |
| Vola | The standard deviation of daily log returns extrapolated to the T-trading-day period after the 10-K filing; T ∈ [5, 40, 60]. |
| ΔVola | The change in the standard deviation of a firm's daily stock returns from the symmetric period of T trading days before to after the 10-K filing. |
| **Control Variables** | |
| FFO/Share | FFO scaled by shares outstanding; (NI+SPPE+(DPACREt-DPACREt-1))/CSHO |
| Size | Natural logarithm of total assets; log(AT) |
| Leverage | Ratio of total liabilities to total assets; LT/AT |
| ΔREV | Change in sales; SALEt-SALEt-1 |
| Sales_Growth | Ratio of change in sales to lagged assets; (SALEt-SALEt-1)/ATt-1 |
| Beta | This CAPM-based measure of the systematic risk compared to the market is directly obtained from CRSP and calculated using the methods developed by Scholes and Williams (1977). |
| BTM | Book-to-market ratio of common stock; (TEQ/(AT-LT))+TXDITC-PSTK)/(CSHPRI*PRCC) |
| IO | Shares held by institutional investors from Thomson Reuters divided by the total shares outstanding. |
| Lag_Vola | The stock return volatility of the last T trading days before the 10-K filing. |
| $Vola^{S\&P}$ | The stock return volatility of the S&P 500 for T trading days before the 10-K filing. |
| ΔVolume | The change of a firm's average daily trading volume from the symmetric period of T trading days before to after the 10-K filing. |
| Text_Length | Total number of words in Item 1A or Item 7A of an annual report (excluding stop words). We use the natural logarithm of the number in our regressions. |
| FOG | Gunning Fog score for the text in Item 1A or Item 7A of an annual report (excluding stop words); calculated as: (words per sentence + percent of complex words)*0.4 |

This table describes the variables used and the corresponding Compustat data items.

A.4: Correlation of Risk Factor Topics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Freq_Topic 1 | 1 | | | | | | | | | | | | | | | | | | | |
| (2) Freq_Topic 2 | 0.233 | 1 | | | | | | | | | | | | | | | | | | |
| (3) Freq_Topic 3 | 0.346 | 0.195 | 1 | | | | | | | | | | | | | | | | | |
| (4) Freq_Topic 4 | 0.207 | -0.371 | 0.357 | 1 | | | | | | | | | | | | | | | | |
| (5) Freq_Topic 5 | 0.354 | 0.115 | 0.444 | 0.351 | 1 | | | | | | | | | | | | | | | |
| (6) Freq_Topic 6 | 0.190 | 0.316 | 0.267 | 0.227 | 0.274 | 1 | | | | | | | | | | | | | | |
| (7) Freq_Topic 7 | 0.364 | 0.227 | 0.351 | 0.178 | 0.278 | 0.281 | 1 | | | | | | | | | | | | | |
| (8) Freq_Topic 8 | 0.253 | 0.195 | 0.416 | 0.306 | 0.427 | 0.313 | 0.090 | 1 | | | | | | | | | | | | |
| (9) Freq_Topic 9 | -0.151 | -0.002 | 0.287 | 0.324 | 0.306 | 0.083 | 0.244 | 0.251 | 1 | | | | | | | | | | | |
| (10) Freq_Topic 10 | 0.201 | 0.120 | 0.210 | 0.399 | 0.472 | 0.256 | 0.238 | 0.248 | 0.243 | 1 | | | | | | | | | | |
| (11) Freq_Topic 11 | 0.268 | 0.205 | 0.177 | 0.211 | 0.038 | 0.410 | 0.314 | 0.293 | 0.153 | 0.173 | 1 | | | | | | | | | |
| (12) Freq_Topic 12 | 0.032 | 0.056 | 0.280 | 0.281 | 0.409 | -0.120 | 0.071 | 0.148 | 0.211 | 0.267 | -0.629 | 1 | | | | | | | | |
| (13) Freq_Topic 13 | 0.302 | 0.390 | 0.177 | 0.244 | 0.407 | 0.408 | 0.235 | 0.066 | 0.084 | 0.305 | 0.134 | 0.128 | 1 | | | | | | | |
| (14) Freq_Topic 14 | 0.165 | 0.382 | 0.366 | -0.030 | 0.149 | -0.062 | 0.159 | 0.110 | 0.185 | -0.030 | -0.001 | 0.354 | -0.284 | 1 | | | | | | |
| (15) Freq_Topic 15 | 0.106 | 0.208 | -0.068 | 0.241 | 0.253 | 0.329 | 0.203 | 0.234 | 0.224 | 0.189 | 0.231 | 0.128 | 0.177 | 0.303 | 1 | | | | | |
| (16) Freq_Topic 16 | -0.070 | 0.115 | 0.363 | 0.221 | -0.005 | 0.091 | 0.247 | 0.088 | 0.216 | 0.073 | 0.307 | 0.043 | 0.112 | 0.172 | 0.042 | 1 | | | | |
| (17) Freq_Topic 17 | -0.0002 | 0.155 | 0.071 | 0.123 | 0.041 | 0.131 | 0.176 | 0.217 | 0.194 | 0.241 | 0.276 | 0.060 | 0.111 | 0.113 | 0.232 | 0.171 | 1 | | | |
| (18) Freq_Topic 18 | 0.161 | 0.127 | 0.264 | 0.298 | 0.259 | 0.131 | -0.502 | 0.396 | 0.131 | 0.167 | 0.226 | 0.078 | 0.069 | 0.303 | 0.136 | 0.001 | 0.092 | 1 | | |
| (19) Freq_Topic 19 | 0.055 | 0.149 | 0.295 | 0.235 | 0.251 | 0.237 | 0.213 | 0.312 | 0.122 | 0.235 | 0.152 | 0.203 | -0.145 | 0.426 | 0.228 | -0.129 | 0.020 | 0.227 | 1 | |
| (20) Freq_Topic 20 | 0.163 | 0.062 | 0.284 | 0.289 | 0.214 | 0.152 | 0.206 | 0.320 | 0.267 | 0.182 | 0.265 | 0.170 | 0.161 | 0.112 | 0.262 | 0.186 | 0.272 | 0.228 | 0.065 | 1 |

This table shows the Bravais-Pearson correlation coefficients of the logged frequencies for the twenty risk factor topics of Item 1A (Freq_Topics).

A.5: Short Risk Description

| **Example** |
| --- |
| **1. Bluerock Residential Growth REIT, Inc., 2010:** |
| Item 1A. Risk Factors We have omitted a discussion of risk factors because, as a smaller reporting company, we are not required to provide such information. For a discussion of the significant factors that make an investment in our shares risky, see the prospectus that relates to our ongoing Initial Public Offering. (48 words) |
| **2. Medalist Diversified REIT, Inc., 2019:** |
| ITEM 1A. RISK FACTORS We have omitted a discussion of risk factors because, as a smaller reporting company, we are not required to provide such information. (22 words) |
| **3. Paragon Real Estate Equity & Investment Trust, 2009:** |
| Item 1A. Risk Factors. This annual report contains historical information, as well as forward-looking statements that involve known and unknown risks and relate to future events, our future financial performance, or our expected future operations and actions. In some cases, you can identify forward-looking statements by terminology such as "may," "will," "should," "expect," "plan," "anticipate," "believe," "estimate," "future," "intend," "could," "hope," "predict," "target," "potential," or "continue" or the negative of these terms or other similar expressions. These forward-looking statements are only our predictions based upon current information and involve numerous assumptions, risks and uncertainties. Our actual results or actions may differ materially from these forward-looking statements for many reasons. While it is impossible to identify all of these factors, the following could cause actual results to differ materially from those estimated by us: worsening of national economic conditions, including continuation of lack of liquidity in the capital markets and more stringent lending requirements by financial institutions; depressed values for commercial real estate properties and companies; changes in local market conditions due to changes in general or local economic conditions and neighborhood characteristics; changes in interest rates and in the availability, cost and terms of mortgage funds; impact of present or future environmental legislation and compliance with environmental laws; ongoing need for capital improvements, particularly in older properties; more attractive lease incentives offered by competitors in similar markets; increased market demand for newer properties; changes in real estate tax rates and other operating expenses; decreases in market prices of the shares of publicly traded real estate companies; adverse changes in governmental rules and fiscal policies; adverse changes in zoning laws; and other factors which are beyond our control. Table of Contents In addition, an investment in the Company involves numerous risks that potential investors should consider carefully, including, without limitation: we have no operating assets; our cash resources are limited; we have a history of losses; we have not raised funds through a public equity offering; our trustees control a significant percentage of our voting shares; shareholders could experience possible future dilution through the issuance of additional shares; we are dependent on a small number of key senior professionals who are part-time employees; and we currently do not plan to distribute dividends to the holders of our shares. (374 words) |

This table shows 3 instances of Item 1A for a low number of words since there is no legal requirement for small firms to do that (Example 1 and Example 2) or the risk factors are very short described (Example 3). Stop words are not excluded from these examples.

Table A.6: Probability of Appearance – Risk Perception measured by the Change in Volatility

| | Model 1 (0, 5 days) | Model 2 (0, 40 days) | Model 3 (0, 60 days) |
|---|---|---|---|
| Freq_Topic 1 | -0.008*** | -0.017*** | -0.016*** |
| *Transaction* | (0.003) | (0.005) | (0.005) |
| Freq_Topic 2 | 0.034*** | 0.030*** | 0.033*** |
| *Regulation* | (0.004) | (0.007) | (0.007) |
| Freq_Topic 3 | -0.009*** | -0.002 | -0.005 |
| *Business Process* | (0.002) | (0.005) | (0.004) |
| Freq_Topic 4 | 0.041*** | 0.030*** | 0.033*** |
| *Unsecured Claims and Debts* | (0.004) | (0.008) | (0.007) |
| Freq_Topic 5 | 0.008*** | 0.007 | 0.006 |
| *Rating* | (0.003) | (0.005) | (0.005) |
| Freq_Topic 6 | -0.001 | -0.009* | -0.008* |
| *Tax and Capital Contribution* | (0.002) | (0.005) | (0.005) |
| Freq_Topic 8 | -0.012*** | -0.008** | -0.011*** |
| *Capital Products and Market* | (0.002) | (0.004) | (0.004) |
| Freq_Topic 9 | 0.002 | -0.006 | -0.005 |
| *Acquisition* | (0.002) | (0.005) | (0.005) |
| Freq_Topic 10 | -0.002** | 0.003 | 0.003 |
| *Contingencies* | (0.001) | (0.002) | (0.002) |
| Freq_Topic 12 | 0.00000 | -0.006 | -0.004 |
| *IT* | (0.002) | (0.003) | (0.003) |
| Freq_Topic 13 | -0.020*** | -0.009* | -0.012** |
| *Legal & Litigation Risk* | (0.002) | (0.005) | (0.005) |
| Freq_Topic 15 | -0.012*** | 0.014*** | 0.014*** |
| *Single Tenant Risk* | (0.002) | (0.005) | (0.005) |
| Freq_Topic 16 | -0.008*** | -0.004 | -0.006 |
| *Property* | (0.002) | (0.004) | (0.004) |
| Freq_Topic 17 | -0.005*** | -0.007 | -0.006 |
| *Politics* | (0.002) | (0.004) | (0.004) |
| Freq_Topic 19 | -0.013*** | -0.008 | -0.007 |
| *Cash-flow* | (0.002) | (0.005) | (0.005) |
| Freq_Topic 20 | 0.003 | 0.003 | 0.004 |
| *Location* | (0.002) | (0.005) | (0.004) |
| FFO/Share | 0.0004 | 0.001 | 0.0002 |
| | (0.001) | (0.002) | (0.002) |
| Size | 0.002 | 0.015* | 0.014** |
| | (0.004) | (0.008) | (0.007) |
| Leverage | 0.016 | -0.006 | -0.018 |
| | (0.014) | (0.029) | (0.029) |
| ΔREV | 0.00000 | -0.00001 | -0.00001 |
| | (0.00001) | (0.00002) | (0.00002) |
| Sales_Growth | 0.006 | -0.008 | -0.010 |
| | (0.005) | (0.009) | (0.009) |
| Beta | -0.001 | 0.001 | -0.010 |
| | (0.004) | (0.008) | (0.007) |
| BTM | -0.018*** | 0.069*** | 0.082*** |
| | (0.002) | (0.006) | (0.006) |
| IO | -0.009 | -0.033** | -0.025* |
| | (0.007) | (0.014) | (0.013) |
| $Vola^{S\&P}$ | -0.208 | -0.696*** | -0.464** |
| | (0.138) | (0.230) | (0.208) |
| ΔVolume | 0.011*** | 0.020*** | 0.020*** |
| | (0.002) | (0.004) | (0.004) |
| Text_Length | -0.009* | 0.010 | 0.005 |
| | (0.005) | (0.010) | (0.010) |
| FOG | -0.001 | -0.002 | -0.001 |
| | (0.002) | (0.004) | (0.004) |
| VIF Min | 1.065 | 1.063 | 1.066 |
| VIF Max | 3.724 | 4.802 | 5.703 |
| N | 1,228 | 1,224 | 1,223 |
| $R^2$ | 0.230 | 0.177 | 0.223 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 1A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (ΔVola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3). The descriptive statistics of ΔVola are given in Table A.7 in Appendix A. The definition of all variables is presented in Table A.3.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Descriptive Statistics – Change in Volatility

| | N | Mean | StDev | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Dependent Variables | | | | | | | | |
| ΔVola (0, 5 days) | 1,543 | 0.001 | 0.044 | -0.324 | -0.012 | 0.001 | 0.014 | 1.114 |
| ΔVola (0, 40 days) | 1,529 | 0.0003 | 0.102 | -2.238 | -0.021 | -0.003 | 0.013 | 2.023 |
| ΔVola (0, 60 days) | 1,519 | -0.007 | 0.106 | -2.229 | -0.029 | -0.004 | 0.015 | 1.993 |

This table shows the change in the standard deviation of a firm's daily stock returns from the symmetric period of T trading-days before to after the 10-K is filed (ΔVola). $N$ is the number of observations, StDev stands for standard deviation, $Q1$ is the first and $Q3$ the third quartile of the distribution, and Min is the minimum and Max is the maximum of each variable. $N$ is set to the maximal available number of observations for each variable.

Table A.8: Comparison of STM, CTM, and LDA – Risk Perception

| | STM | CTM | LDA | STM | CTM | LDA |
|---|---|---|---|---|---|---|
| Abs_Allocation 1 | -0.007*** | 0.001 | 0.0001 | -0.015*** | -0.001 | 0.0005 |
| | (0.002) | (0.004) | (0.001) | (0.005) | (0.008) | (0.001) |
| Abs_Allocation 2 | 0.032*** | 0.007 | 0.001 | 0.030*** | -0.009 | 0.001 |
| | (0.003) | (0.005) | (0.001) | (0.007) | (0.011) | (0.001) |
| Abs_Allocation 3 | -0.011*** | -0.009 | -0.0001 | -0.006 | 0.002 | 0.0001 |
| | (0.002) | (0.006) | (0.001) | (0.004) | (0.011) | (0.001) |
| Abs_Allocation 4 | 0.038*** | -0.013* | -0.001 | 0.031*** | -0.007 | -0.002 |
| | (0.003) | (0.008) | (0.001) | (0.007) | (0.016) | (0.002) |
| Abs_Allocation 5 | 0.009*** | 0.009** | 0.0001 | 0.008* | 0.006 | 0.0003 |
| | (0.002) | (0.004) | (0.001) | (0.005) | (0.008) | (0.002) |
| Abs_Allocation 6 | -0.001 | -0.001 | -0.0004 | -0.009** | -0.001 | -0.00004 |
| | (0.002) | (0.003) | (0.001) | (0.004) | (0.007) | (0.001) |
| Abs_Allocation 7 | | -0.011 | -0.001 | | -0.016 | -0.001 |
| | | (0.008) | (0.001) | | (0.017) | (0.002) |
| Abs_Allocation 8 | -0.010*** | -0.004 | 0.001** | -0.008** | 0.004 | 0.0001 |
| | (0.002) | (0.003) | (0.001) | (0.003) | (0.007) | (0.001) |
| Abs_Allocation 9 | 0.002 | -0.006 | 0.00003 | -0.004 | -0.011 | -0.001 |
| | (0.002) | (0.005) | (0.0005) | (0.004) | (0.011) | (0.001) |
| Abs_Allocation 10 | -0.002*** | 0.002 | 0.001 | 0.001 | -0.001 | 0.003 |
| | (0.001) | (0.004) | (0.001) | (0.002) | (0.007) | (0.002) |
| Abs_Allocation 11 | | 0.002 | 0.001 | | 0.004 | 0.001 |
| | | (0.003) | (0.001) | | (0.005) | (0.003) |
| Abs_Allocation 12 | 0.00001 | -0.006 | 0.0003 | -0.004 | -0.011 | 0.001 |
| | (0.001) | (0.005) | (0.001) | (0.003) | (0.009) | (0.001) |
| Abs_Allocation 13 | -0.017*** | 0.016*** | -0.0004 | -0.010** | 0.015 | -0.001 |
| | (0.002) | (0.005) | (0.001) | (0.005) | (0.011) | (0.002) |
| Abs_Allocation 14 | | -0.004 | 0.0001 | | 0.014 | 0.003* |
| | | (0.011) | (0.001) | | (0.022) | (0.001) |
| Abs_Allocation 15 | -0.012*** | 0.010*** | -0.002*** | 0.010** | 0.008 | -0.005*** |
| | (0.002) | (0.003) | (0.001) | (0.004) | (0.005) | (0.001) |
| Abs_Allocation 16 | -0.007*** | 0.005 | -0.0004 | -0.005 | -0.008 | 0.0005 |
| | (0.002) | (0.005) | (0.001) | (0.004) | (0.011) | (0.003) |
| Abs_Allocation 17 | -0.005*** | -0.006 | -0.001 | -0.004 | -0.012 | -0.002 |
| | (0.002) | (0.005) | (0.001) | (0.004) | (0.011) | (0.002) |
| Abs_Allocation 18 | | 0.0001 | -0.00004 | | -0.003 | -0.0001 |
| | | (0.004) | (0.001) | | (0.009) | (0.001) |
| Abs_Allocation 19 | -0.012*** | -0.002 | 0.001 | -0.006 | -0.002 | 0.001 |
| | (0.002) | (0.005) | (0.001) | (0.005) | (0.010) | (0.001) |
| Abs_Allocation 20 | 0.003 | 0.020 | -0.001* | 0.004 | 0.080 | -0.001 |
| | (0.002) | (0.026) | (0.001) | (0.004) | (0.054) | (0.001) |
| FFO/Share | 0.001 | 0.0001 | 0.0001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Size | 0.001 | 0.0004 | -0.0002 | 0.013* | 0.004 | 0.004 |
| | (0.003) | (0.003) | (0.003) | (0.007) | (0.007) | (0.007) |
| Leverage | 0.029** | 0.012 | 0.018 | 0.007 | -0.025 | -0.004 |
| | (0.012) | (0.013) | (0.013) | (0.027) | (0.028) | (0.027) |
| ΔREV | 0.00000 | 0.00000 | 0.00000 | -0.00002 | -0.00002 | -0.00002 |
| | (0.00001) | (0.00001) | (0.00001) | (0.00002) | (0.00002) | (0.00002) |
| Sales_Growth | 0.005 | 0.004 | 0.002 | -0.006 | -0.008 | -0.007 |
| | (0.004) | (0.004) | (0.004) | (0.009) | (0.009) | (0.009) |
| Beta | 0.009*** | 0.011*** | 0.010*** | 0.015** | 0.023*** | 0.020*** |
| | (0.003) | (0.004) | (0.004) | (0.007) | (0.008) | (0.007) |
| BTM | -0.020*** | -0.020*** | -0.019*** | 0.066*** | 0.065*** | 0.065*** |
| | (0.002) | (0.002) | (0.002) | (0.006) | (0.006) | (0.006) |
| IO | -0.018*** | -0.016** | -0.019*** | -0.038*** | -0.034*** | -0.038*** |
| | (0.006) | (0.006) | (0.006) | (0.013) | (0.013) | (0.013) |
| Lag_Vola | 0.354*** | 0.310*** | 0.328*** | 0.521*** | 0.501*** | 0.516*** |
| | (0.037) | (0.040) | (0.040) | (0.043) | (0.044) | (0.043) |
| $Vola^{S\&P}$ | 0.866*** | 0.885*** | 0.893*** | 1.290*** | 1.328*** | 1.278*** |
| | (0.133) | (0.145) | (0.145) | (0.305) | (0.310) | (0.310) |
| ΔVolume | 0.007*** | 0.007*** | 0.006*** | 0.020*** | 0.023*** | 0.020*** |
| | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) | (0.004) |
| Text_Length | -0.005 | -0.011 | -0.0003 | -0.001 | -0.034 | 0.008 |
| | (0.005) | (0.019) | (0.005) | (0.010) | (0.039) | (0.010) |
| FOG | -0.0003 | -0.0004 | 0.0003 | 0.00004 | 0.001 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) | (0.004) |
| VIF Min | 1.065 | 1.044 | 1.0876 | 1.065 | 1.032 | 1.073 |
| VIF Max | 3.724 | 5.163 | 3.733 | 5.703 | 6.379 | 5.786 |
| N | 1,228 | 1,228 | 1,228 | 1,223 | 1,223 | 1,223 |
| $R^2$ | 0.345 | 0.234 | 0.229 | 0.283 | 0.268 | 0.274 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 1A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1) and 60 trading days (Model 3). The variable Abs_Allocation is derived using three different machine assisted approaches (i.e. STM, CTM, and LDA). Each approach applies a 20 topic full model to identify and quantify the risks disclosed in Item 1A. The risk topics identified by STM, CTM, and LDA are not identical. The definition of all variables is presented in Table A.3 in Appendix A.

# Appendix B

## LDA Topics and Metadata Covariates

We apply the standard LDA and identify the top words for 20 topics analogously to the STM method for Item 1A. Table B.1 in Appendix B presents the results of this clustering. As assumed given by the optimization criterion of the LDA, the topics are close to investment foci, such as Topic #1 corresponds to "Health Care", Topic #4 to "Residential", and Topic #9 to "Retail" to name a few. LDA identifies the foci as the most substantial distinction within the textual corpus and allocates them as latent topics.

We further regress the investment foci (i.e. Ziman property types) on each of the 20 topics, in order to analyze whether the frequency of appearance for the individual risk factors is associated with property types (see Table B.2 in Appendix B). We find, for example, that 5 out of 7 Ziman property types are statistically significantly associated with Topic #8 "Infrastructure". A positive coefficient sign suggests that a REIT assigned to the respective property type (e.g., "Unclassified") is likely to allocate a larger proportion of its risk disclosure to Topic #8. On the contrary, the negative relationship indicates that Topic #8 is less likely to occur in filings of REITs which are classified as "Residential", "Health Care“, or "Self Storage". The relationship between property type and the probability of appearance for a risk-factor topic shows that we need to consider document-specific metadata (i.e. property types) when using a machine to identify the risk factors discussed by a REIT.

B.1: LDA Top Word List

| |
|---|
| **Topic 1: Health Care** |
| healthcare, medicaid, correctional, detention, hospitals, hospital, brookdale, seniors, nursing, physicians, patients, payors, medicare, sunrise, inmates, tenants, care, medical, physician, science |
| **Topic 2: Taxable REIT Subsidiary** |
| spin, manager, bennett, comments, master, trss, trs, separation, stockholders, reits, treated, tenant, charter, arc, emerging, restaurant, tcja, gain, agreement, withholding |
| **Topic 3: Reporting Duties/Auditing** |
| reporting, caption, report, discussion, see, analysis, information, management's, expressions, filer, composed, incorporated, rule, relates, underway, sponsoring, jpmorgan, auditors, oxley, sarbanes |
| **Topic 4: Residential** |
| staff, single-family, hoa, hoas, homes, homeownership, cdo, loans, mortgage, foreclosure, non-performing, servicers, homeowners, residents, rental, securitizations, borrower, borrowers, stockholders, home |
| **Topic 5: Market and Politics** |
| smaller, rules, effecting, collected, disclosure, vendor, weakness, oversight, defined, interim, restate, see, electing, regulation, misstatement, trump, relates, attestation, detected, commission |
| **Topic 6: Investment Universe** |
| advisor, cole, stockholders, wells, ira, erisa, co-ownership, sponsored, estate-related, mezzanine, bridge, manager, sponsor, nav, sale-leaseback, internalization, builders, advisory, tenants |
| **Topic 7: Property and Hurricane** |
| companies, omitted, professionals, managed, information, rita, controls, investing, commodity, ranks, katrina, adequacy, continuance, client, capitalizations, segment, pursue, pose, calculation, disagree |
| **Topic 8: Infrastructure** |
| wireless, towers, disclose, tower, antenna, sprint, billboards, t-mobile, nols, radio, advertising, verizon, att, fcc, communications, nextel, roaming, lighting, broadcast, theatres |
| **Topic 9: Retail** |
| host, incs, penn, mall, centers, shopping, separation, entirety, anchor, stores, sears, gaming, outlet, cam, anchors, retailers, malls, retail, lps, shareholders |
| **Topic 10: Cyber Criminality** |
| systems, security, information, technology, confidential, cyber, computer, networks, identifiable, breaches, data, arisk, unauthorized, cyber-attacks, reputation, electronic, store, hackers, shutdowns, software |
| **Topic 11: Stock Market/Partnerships** |
| stockholders, directors, stockholder, risky, partnership, military, privatization, million, preferred, units, warrants, agreement, andrew, messrs, llc, quoted, approximately, vice, executive, combination |
| **Topic 12: Lodging/Resorts** |
| rmr, included, tas, aic, portnoy, sonesta, stars, trustees, star, adam, gov, irc, travel, hotels, barry, hotel, shareholders, marriott, snh, living |
| **Topic 13: Infrastructure** |
| adviser, depositary, arc, gas, grand, terminal, corridor, infrastructure, decommissioning, sale-leaseback, percent, convertible, commodities, production, investees, privately-held, stockholders, notes, commodity, preferred |

Continued on next page

Table 5.6 – continued from previous page

| **Topic 13: Infrastructure** |
|---|
| adviser, depositary, arc, gas, grand, terminal, corridor, infrastructure, decommissioning, sale-leaseback, percent, convertible, commodities, production, investees, privately-held, stockholders, notes, commodity, preferred |
| **Topic 14: Lodging/Resorts** |
| hotels, hotel, permitted, lodging, travel, room, rooms, franchisors, shareholders, marriott, trustees, franchisor, franchise, revpar, reservations, hilton, leisure, intermediaries, guests, lessees |
| **Topic 15: Company/Real Estate** |
| requested, partnership, stockholders, tenants, space, mgcl, honolulu, directors, units, charter, rental, tenant, stockholder, self-storage, market, partner, asking, leases, airborne, co-venturers |
| **Topic 16: Timber** |
| timber, timberlands, timberland, forest, centers, wood, harvest, species, logs, harvesting, student, connectivity, fiber, logging, data, universities, endangered, hbu, campus, colocation |
| **Topic 17: Residential** |
| communities, apartment, digital, companys, multifamily, realty, housing, freddie, incs, fannie, mac, homes, mae, residents, sale, lps, manufactured, multi-family, excel, partnership |
| **Topic 18: REIT Specifics** |
| vornado, trustees, shareholders, alexanders, shareholder, gladstone, roth, transitional, declaration, toys, trust, tenants, mandelbaum, wight, maryland, interstate, space, partnership, zell, realty |
| **Topic 19: Retail** |
| anchor, shopping, tenants, space, retail, shareholders, centers, self-storage, retailers, tenant, stores, leases, redevelopment, predictions, bankruptcy, rental, retailing, re-lease, development, venture |
| **Topic 20: Property Risk and Terrorism** |
| page, securityholders, science, tenants, space, industrial, ofac, manhattan, asbestos, avenue, ifrs, co-investment, tria, indoor, unconsolidated, earthquake, ventures, nbcr, unsecured, partnership |

This table shows the top 20 words for each of the topics.

B.2: Regressions for LDA and Property Focus

| Variable | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 | Topic 6 | Topic 7 | Topic 8 | Topic 9 | Topic 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.038*** | 0.0641*** | 0.0282*** | 0.0062 | 0.004 | 0.0759*** | 0.0584*** | 0.0673*** | 0.0714*** | 0.0556*** |
| | (0.0141) | (0.0144) | (0.0103) | (0.011) | (0.004) | (0.0132) | (0.0116) | (0.014) | (0.0134) | (0.0134) |
| Health Care | 0.0205 | 0.0428* | -0.0041 | -0.0029 | -0.0023 | -0.0197 | 0.0071 | -0.0482** | -0.0122 | -0.0098 |
| | (0.0203) | (0.0224) | (0.0155) | (0.016) | (0.0056) | (-0.0205) | (0.017) | (-0.0193) | (-0.0203) | (0.0201) |
| Industrial/Office | 0.0315* | 0.0021 | 0.0119 | 0.031** | 0.0232*** | -0.0378** | -0.0264* | -0.0307* | -0.0311* | 0.0326* |
| | (0.0176) | (0.0184) | (0.0129) | (0.0138) | (0.0066) | (-0.0161) | (0.0142) | (-0.0167) | (-0.0165) | (0.0184) |
| Lodging/Resorts | 0.0237 | 0.0225 | -0.0167 | 0.0699*** | -0.0036 | -0.0392** | -0.0385** | -0.0174 | -0.0247 | 0.0065 |
| | (0.0198) | (0.0212) | (0.0136) | (0.0165) | (0.0054) | (-0.0189) | (0.0158) | (-0.0186) | (-0.018) | (0.0203) |
| Residential | -0.0003 | -0.0357* | 0.0087 | 0.0398** | 0.0103 | -0.0241 | -0.0075 | -0.0549*** | -0.0212 | 0.0065 |
| | (0.0191) | (0.0193) | (0.0141) | (0.0156) | (0.0065) | (-0.0173) | (0.0162) | (-0.0181) | (-0.0186) | (0.0185) |
| Retail | -0.0103 | -0.0136 | 0.0039 | 0.0647*** | -0.003 | -0.0456*** | -0.025* | -0.0245 | -0.0434** | -0.007 |
| | (0.0174) | (0.018) | (0.0122) | (0.0139) | (0.0048) | (-0.0162) | (0.0147) | (-0.0163) | (-0.0169) | (0.017) |
| Self Storage | 0.0171 | -0.0611** | -0.0266 | -0.002 | -0.0021 | 0.0834*** | -0.0442* | -0.0567** | 0.0796** | 0.0099 |
| | (0.0275) | (0.0275) | (0.0191) | (0.0221) | (0.008) | (0.0315) | (0.0234) | (-0.026) | (0.0331) | (0.0325) |
| Unclassified | 0.047** | -0.0283 | 0.0308** | -0.0022 | 0.0005 | -0.049*** | -0.033** | 0.0591*** | -0.0262 | -0.007 |
| | (0.0192) | (0.0196) | (0.0149) | (0.015) | (0.0054) | (-0.0179) | (0.0166) | (0.0205) | (-0.0178) | (0.0188) |

| Variable | Topic 11 | Topic 12 | Topic 13 | Topic 14 | Topic 15 | Topic 16 | Topic 17 | Topic 18 | Topic 19 | Topic 20 |
|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.0332*** | 0.0378** | 0.0417*** | 0.0273*** | 0.023* | 0.0896*** | 0.0633*** | 0.0566*** | 0.0671*** | 0.0912*** |
| | (0.0101) | (0.0152) | (0.015) | (0.0093) | (0.0137) | (0.0166) | (0.0147) | (0.0152) | (0.0156) | (0.0156) |
| Health Care | -0.0118 | -0.0175 | 0.0496** | -0.0006 | 0.0459** | -0.016 | -0.0055 | 0.0065 | 0.004 | -0.0254 |
| | (0.0148) | (0.0219) | (0.0229) | (0.0133) | (0.0197) | (0.0242) | (0.0218) | (0.0227) | (0.0221) | (0.0215) |
| Industrial/Office | 0.0092 | -0.0043 | 0.0419** | -0.0111 | 0.0285 | -0.05** | -0.0283 | 0.0478** | 0.0085 | -0.0481** |
| | (0.0129) | (0.0191) | (0.0193) | (0.0116) | (0.0178) | (0.0204) | (0.0183) | (0.0198) | (0.0194) | (0.0189) |
| Lodging/Resorts | 0.0039 | 0.0554*** | 0.0095 | -0.0243* | 0.0121 | -0.0067 | 0.0161 | -0.0079 | -0.0293 | -0.0111 |
| | (0.0145) | (0.0208) | (0.0205) | (0.0125) | (0.0189) | (0.022) | (0.0211) | (0.0219) | (0.0206) | (0.0225) |
| Residential | 0.0175 | 0.0324 | 0.015 | -0.0024 | 0.004 | 0.0107 | 0.0237 | 0.0006 | -0.0234 | 0.0004 |
| | (0.016) | (0.0212) | (0.0208) | (0.0139) | (0.0186) | (0.0227) | (0.0207) | (0.0209) | (0.0207) | (0.0207) |
| Retail | -0.0245** | 0.0801*** | 0.0583*** | 0.0208* | 0.0507*** | -0.0581*** | -0.0111 | 0.0449** | 0.0018 | -0.0584*** |
| | (0.0121) | (0.0192) | (0.0198) | (0.0121) | (0.0174) | (0.0198) | (0.0181) | (0.0193) | (0.0198) | (0.0185) |
| Self Storage | -0.0218 | 0.0809** | -0.0391 | -0.0248 | 0.0299 | -0.0762** | 0.0938*** | -0.0495* | 0.0949*** | -0.0854*** |
| | (0.0207) | (0.0319) | (0.0298) | (0.018) | (0.0271) | (0.0312) | (0.0333) | (0.0298) | (0.0327) | (0.0281) |
| Unclassified | 0.009 | 0.0155 | 0.0086 | 0.0029 | 0.0506*** | 0.0404* | -0.0052 | -0.0325 | -0.0221 | -0.058*** |
| | (0.014) | (0.021) | (0.0207) | (0.0133) | (0.0187) | (0.0229) | (0.021) | (0.0206) | (0.0213) | (0.0205) |

This table shows the relationship between metadata (investment foci) and topics. The topic proportions are the dependent variables of a regression which shows the conditional expectation of topic prevalence given document characteristics, so that the estimation uncertainty is incorporated in the dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Appendix C

## Risk Perception for Item 7A

The second risk section included in the 10-K is represented by Item 7A. This section should list "quantitative and qualitative disclosures about market risk" which are relevant for a company (e.g., interest rate risk or foreign currency exchange risk). We conduct our analyses additionally for this section describing more long-term risk.

In the first step, we apply the STM to Item 7A and label the topics. Since Item 7A is shorter, we set the number of topics to be identified by the STM to 5. Following the SECs' requirement (Item 305 of Regulation S-K (§ 229.305)) to inform the public on market risk, the risk topics describe more long-term risks like "Politics & Regions" or "(Re-)financing" (see Table C.1 in Appendix C). The descriptive statistics of Abs_Allocation are given in Table C.2.

In the second step, we apply the fixed-effect panel regression model as stated in Section 4 to Item 7A, to address Hypotheses 1 and 2. The results are given in Table C.3 in Appendix C. Our results suggest that the extracted risk factors are less informative for this item than those identified in Item 1A – none of the 5 factors is significant for the short-term (5 day) window. If we change to longer windows, three risk topics become significant. We conclude that this goes in line with the more long-term nature of the risk factors described in Item 7A. The goodness of fit is for all windows smaller than for Item 1A – ranging from 14% to 21% instead of 21% to 35%. This can be explained by the composition of Item 7A, since this section not only names but additionally quantifies the impact of the individual risk factors on future firm performance. Thus, managers usually use numbers to describe how risk factors affect firms' filings in this section. However, our method focuses on textual data i.e. the words used to qualitatively describe relevant risks and topic models cannot take numbers into account. In addition, with an average length of only 6,680 words, Item 7A is just a tenth of the average length of Item 1A. As explained by Papilloud and Hinneburg (2018), shorter documents decrease the robustness of the topic model, because it "learns" less from the data. Third, many documents have (almost) the same content, which further distorts the topic model (Papilloud and Hinneburg, 2018).

C.1: STM Top Word Lists for Item 7A

| **Topic 1: Contractual Risks** |
|---|
| discounted, excluding, one-month, fix, agreements, policy, notional, maturities, effectively, contractual, techniques, weighted-average, corresponding, giving, reflects, rating, transactions, fixes, discount, fees |
| **Topic 2: Accounting** |
| liability, direct, eliminated, actively, stock, accrued, amounted, plan, relating, carried, years, recognized, sale, liquidation, statements, statement, investing, accounts, permanent, carrying |
| **Topic 3: Capital** |
| segments, redeemable, capitalized, section, venture, immediately, regarding, act, joint, redemption, acquired, discussions, consolidation, disclosure, projects, iii, general, reference, receivable, common |
| **Topic 4: Politics and Regions** |
| refers, political, monetary, domestic, international, structure, considering, beyond, governmental, considerations, factors, many, economic, prices, event, financings, take, unable, high, dependent |
| **Topic 5: (Re-)financing** |
| flexibility, refinance, opportunity, issue, change, present, matures, unsecured, although, refinancing, assuming, principal, respect, near, term, revolving, exceeds, premiums, mitigate, time |

This table shows the top 20 words for each of the topics.

C.2: Descriptive Statistics – Absolute Allocation of Words for Item 7A

| | N | Mean | StDev | Min | Q1 | Median | Max |
|---|---|---|---|---|---|---|---|
| Abs_Allocation 1 | 2,514 | 1,237.987 | 2,987.863 | 0.965 | 12.295 | 51.106 | 42,934.940 |
| Abs_Allocation 2 | 2,514 | 2,075.822 | 23,277.310 | 0.573 | 3.710 | 10.673 | 436,479.300 |
| Abs_Allocation 3 | 2,514 | 1,101.688 | 12,891.150 | 0.958 | 5.486 | 13.465 | 373,974.400 |
| Abs_Allocation 4 | 2,514 | 1,048.147 | 2,079.992 | 3.164 | 14.860 | 79.551 | 37,108.090 |
| Abs_Allocation 5 | 2,514 | 1,198.234 | 3,656.759 | 0.418 | 6.859 | 31.509 | 94,708.970 |

This table shows the descriptive statistics for the frequencies (in %) for the risk factor topics multiplied by the total length of the corresponding disclosure (Abs_Allocation). N is the number of observations, StdDev stands for standard deviation, Q1 is the first and Q3 the third quartile of the distribution, and Min is the minimum and Max the maximum of each variable. N is set to the maximal available number of observations for each variable.

C.3: Absolute Allocation of Words – Risk Perception for Item 7A

| | Model | | |
|---|---|---|---|
| | Model 1 (0, 5 days) | Model 2 (0, 40 days) | Model 3 (0, 60 days) |
| Abs_Allocation 1 | -0.001 | -0.011*** | -0.009** |
| *Contractual Risks* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 2 | -0.0001 | -0.001 | -0.001 |
| *Accounting* | (0.001) | (0.003) | (0.003) |
| Abs_Allocation 3 | -0.00001 | -0.002 | -0.003 |
| *Capital* | (0.001) | (0.003) | (0.003) |
| Abs_Allocation 4 | 0.001 | 0.013*** | 0.012*** |
| *Politics and Regions* | (0.002) | (0.004) | (0.004) |
| Abs_Allocation 5 | -0.002 | -0.008** | -0.009** |
| *(Re-)financing* | (0.002) | (0.004) | (0.0001) |
| FFO/Share | 0.00005 | 0.001 | |
| | (0.001) | (0.002) | (0.002) |
| Size | -0.001 | 0.011 | |
| | (0.003) | (0.008) | (0.008) |
| Leverage | 0.021 | -0.013 | |
| | (0.013) | (0.031) | (0.030) |
| $\Delta$ REV | 0.00000 | -0.00001 | |
| | (0.00001) | (0.00002) | (0.00002) |
| Sales_Growth | 0.005 | 0.005 | |
| | (0.004) | (0.010) | (0.010) |
| Beta | 0.008** | 0.033*** | |
| | (0.004) | (0.008) | (0.008) |
| BTM | -0.015*** | 0.005 | 0.017*** |
| | (0.002) | (0.006) | (0.006) |
| IO | -0.019*** | -0.051*** | -0.045*** |
| | (0.006) | (0.015) | (0.015) |
| Lag_Vola | 0.315*** | 0.355*** | 0.503*** |
| | (0.041) | (0.066) | (0.049) |
| $Vola^{S\&P}$ | 0.954*** | 1.540*** | 1.228*** |
| | (0.148) | (0.342) | (0.354) |
| $\Delta$ Volume | 0.006*** | 0.021*** | 0.021*** |
| | (0.002) | (0.005) | (0.005) |
| Text_Length | 0.002 | 0.030*** | 0.029*** |
| | (0.003) | (0.007) | (0.007) |
| FOG | -0.0001 | -0.004** | -0.004** |
| | (0.001) | (0.002) | (0.002) |
| VIF Min | 1.033 | 1.022 | 1.037 |
| VIF Max | 3.670 | 4.594 | 5.084 |
| N | 1,209 | 1,205 | 1,204 |
| $R^2$ | 0.195 | 0.144 | 0.211 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 7A. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1), 40 trading days (Model 2), and 60 trading days (Model 3).

# Appendix D

D.1: Descriptive Statistics

| | N | Mean | StDev | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Control Variables | | | | | | | | |
| FFO/Share | 388 | 1.673 | 2.933 | -7.408 | 0.483 | 1.166 | 2.215 | 37.746 |
| Size | 388 | 7.774 | 1.297 | 2.316 | 7.037 | 7.806 | 8.571 | 10.411 |
| Leverage | 388 | 0.599 | 0.173 | 0.001 | 0.505 | 0.602 | 0.687 | 1.468 |
| $\Delta$ REV | 388 | 75.044 | 240.854 | -1,214.064 | 3.172 | 25.684 | 95.635 | 2,143.65 |
| Sales_Growth | 388 | 0.026 | 0.088 | -0.800 | 0.003 | 0.015 | 0.037 | 0.876 |
| Beta | 388 | 0.908 | 0.405 | -0.362 | 0.627 | 0.869 | 1.184 | 2.311 |
| BTM | 388 | -0.032 | 0.117 | -1.037 | 0.00004 | 0.001 | 0.004 | 0.119 |
| $Vola^{S\&P}$ (-5, 0 days) | 388 | 0.020 | 0.014 | 0.004 | 0.011 | 0.017 | 0.025 | 0.089 |
| $Vola^{S\&P}$ (-60, 0 days) | 388 | 0.070 | 0.035 | 0.030 | 0.052 | 0.056 | 0.081 | 0.192 |
| $\Delta$ Volume (0, 5 days) | 388 | 0.078 | 1.233 | -6.529 | -0.111 | 0.008 | 0.113 | 16.667 |
| $\Delta$ Volume (0, 60 days) | 388 | 0.043 | 0.618 | -6.705 | -0.088 | -0.002 | 0.095 | 4.375 |
| Text_Length | 388 | 10.981 | 0.714 | 5.568 | 10.653 | 11.035 | 11.344 | 13.155 |
| FOG | 388 | 22.585 | 1.185 | 19.455 | 21.824 | 22.5 | 23.228 | 27.276 |
| Dependent Variables | | | | | | | | |
| Vola (0, 5 days) | 388 | 0.044 | 0.069 | 0.003 | 0.021 | 0.033 | 0.047 | 1.129 |
| Vola (0, 60 days) | 388 | 0.143 | 0.117 | 0.054 | 0.087 | 0.109 | 0.146 | 1.120 |

This table shows the descriptive statistics for the variables and dependent variables (Vola) for the dataset of mortgage and unclassified REITs. The definition of all variables is presented in Table A.3 in Appendix A. N is the number of observations, StdDev stands for standard deviation, and Min is the minimum and Max the maximum of each variable. N is set to the maximal available number of observations for each variable.

D.2: Comparison of STM, CTM, and LDA – Risk Perception

| | Model 1 (0, 5 days) | | | Model 3 (0, 60 days) | | |
|---|---|---|---|---|---|---|
| | STM | CTM | LDA | STM | CTM | LDA |
| Freq_Topic 1 | -0.003 | -0.005** | -0.003 | -0.0001 | -0.007*** | -0.004 |
| | (0.004) | (0.002) | (0.004) | (0.005) | (0.002) | (0.005) |
| Freq_Topic 2 | -0.003 | -0.003* | -0.004 | 0.0001 | -0.001 | 0.001 |
| | (0.003) | (0.002) | (0.006) | (0.004) | (0.002) | (0.007) |
| Freq_Topic 3 | 0.010*** | 0.005*** | -0.009 | 0.008** | 0.005** | -0.012 |
| | (0.003) | (0.002) | (0.008) | (0.004) | (0.002) | (0.009) |
| Freq_Topic 4 | -0.004 | 0.012 | 0.004 | -0.005 | 0.009 | 0.005 |
| | (0.003) | (0.003) | (0.005) | (0.003) | (0.003) | (0.006) |
| Freq_Topic 5 | -0.0003 | -0.001 | -0.001 | -0.0004 | -0.002 | 0.006 |
| | (0.002) | (0.002) | (0.008) | (0.003) | (0.002) | (0.009) |
| Freq_Topic 6 | -0.0005 | -0.003 | 0.013 | -0.001 | -0.002 | 0.009 |
| | (0.003) | (0.004) | (0.010) | (0.004) | (0.005) | (0.011) |
| Freq_Topic 7 | -0.009*** | 0.001 | -0.001 | -0.008** | 0.002 | -0.002 |
| | (0.003) | (0.002) | (0.010) | (0.004) | (0.002) | (0.011) |
| Freq_Topic 8 | -0.011*** | -0.001 | 0.002 | -0.007*** | -0.003 | 0.003 |
| | (0.004) | (0.002) | (0.005) | (0.004) | (0.002) | (0.006) |
| Freq_Topic 9 | 0.009*** | 0.001 | -0.003 | 0.007*** | -0.004 | -0.005 |
| | (0.004) | (0.003) | (0.005) | (0.004) | (0.003) | (0.006) |
| Freq_Topic 10 | 0.075 | -0.001 | -0.001 | 0.024 | -0.0002 | -0.0002 |
| | (0.058) | (0.002) | (0.005) | (0.067) | (0.002) | (0.006) |
| FFO/Share | -0.0001 | 0.0003 | 0.001 | -0.002 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Size | -0.004 | -0.005 | -0.007 | 0.001 | 0.002 | 0.002 |
| | (0.009) | (0.010) | (0.010) | (0.011) | (0.012) | (0.012) |
| Leverage | 0.010 | 0.006 | 0.005 | 0.041 | 0.036 | 0.051 |
| | (0.037) | (0.037) | (0.040) | (0.043) | (0.043) | (0.045) |
| ΔREV | 0.00000 | 0.00001 | 0.00000 | 0.00000 | 0.00001 | -0.00000 |
| | (0.00002) | (0.00002) | (0.00002) | (0.00002) | (0.00002) | (0.00002) |
| Sales_Growth | 0.027 | 0.032 | 0.020 | -0.007 | -0.001 | -0.007 |
| | (0.046) | (0.045) | (0.048) | (0.054) | (0.053) | (0.055) |
| Beta | 0.020* | 0.024** | 0.021* | 0.030** | 0.032*** | 0.026** |
| | (0.011) | (0.010) | (0.011) | (0.013) | (0.012) | (0.013) |
| BTM | -0.118*** | -0.097*** | -0.105*** | -0.118*** | -0.120*** | -0.114** |
| | (0.037) | (0.036) | (0.040) | (0.044) | (0.043) | (0.046) |
| Lag_Vola | 0.055 | 0.064 | 0.062 | 0.584*** | 0.557*** | 0.578*** |
| | (0.141) | (0.139) | (0.143) | (0.076) | (0.074) | (0.076) |
| $Vola^{S\&P}$ | 1.771*** | 1.702*** | 1.783*** | 0.984*** | 0.944*** | 1.053*** |
| | (0.468) | (0.456) | (0.479) | (0.356) | (0.344) | (0.360) |
| ΔVolume | -0.001 | -0.002 | -0.0004 | 0.011* | 0.008 | 0.009 |
| | (0.003) | (0.003) | (0.003) | (0.006) | (0.006) | (0.006) |
| Text_Length | -0.061 | 0.012 | 0.007 | -0.027 | 0.001 | -0.008 |
| | (0.052) | (0.009) | (0.010) | (0.061) | (0.010) | (0.011) |
| FOG | 0.007 | 0.003 | 0.007 | 0.009 | 0.003 | 0.008 |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.008) |
| VIF Min | 1.194 | 1.105 | 1.395 | 1.161 | 1.083 | 1.179 |
| VIF Max | 4.324 | 4.319 | 4.298 | 5.116 | 7.187 | 4.652 |
| N | 388 | 388 | 388 | 388 | 388 | 388 |
| $R^2$ | 0.195 | 0.144 | 0.099 | 0.344 | 0.298 | 0.290 |

This table presents the results of fixed-effect models controlling for unobserved firm and time effects for Item 1A for the dataset of mortgage and unclassified REITs. The table reports panel regression results of fixed effects models, which include coefficients and standard errors (in parentheses) of determinants affecting investor's risk perception. The dependent variable (Vola) takes a different number of trading days after the 10-K filing date into account – 5 trading days (Model 1) and 60 trading days (Model 3). The variable Freq_Topic is derived using three different machine-assisted approaches (i.e., STM, CTM, and LDA). Each approach applies a 10-topic full model to identify and quantify the risks disclosed in Item 1A. The risk topics identified by STM, CTM, and LDA are not identical. The definition of all variables is presented in Table A.3 in Appendix A.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

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# Chapter 6

# How socially irresponsible are socially responsible mutual funds?

This chapter is based on a joint work with Gregor Dorfleitner (University of Regensburg) and Christian Kreuzer (University of Regensburg) and has been published as Dorfleitner, Kreuzer, Laschinger (2021), How socially irresponsible are socially responsible mutual funds?, *Finance Research Letters*, Volume 43, 101990.

**Abstract** Based on a dataset of over 400 fund compositions in the years 2003-2018 this paper analyzes the persistence of controversies scores and environmental, social, governance (ESG) scores in socially responsible US mutual funds. As measurements for corporate social irresponsibility as well as corporate social responsibility activities, it is shown that US mutual funds exhibit controversies and ESG persistence in the short and longer-term. When examining the relationship between controversies and ESG scores in comparison with management fees, it becomes apparent that higher-paid managers achieve better results regarding controversies scoring but worse results regarding ESG scoring, compared to lower-paid managers.

**Keywords** ESG, Controversies, Socially responsible investing, corporate social responsibility

## 6.1 Introduction

For many years socially responsible investing (SRI) has been studied from a practical and academic point of view in a variety of ways. While many companies focus exclusively on promoting and maintaining their corporate social responsibility (CSR) activities, the question remains regarding to what extent corporate social irresponsibility (CSI) is avoided. Even if in today's society CSR activities of companies are gaining increasing attention, since being socially responsible entails not only doing a lot of “good" but also actively avoiding many more “bad" in terms of social irresponsible or unethical behavior, such as environmental scandals or business ethics controversies (see Lin-Hi and Müller (2013)). After all, an examination of CSR criteria alone is not sufficient to discover to which extent certain CSR activities are only used to make amends for past “sins", insure against possible subsequent CSI (see Kang et al. (2016)), or remain part of sustainable corporate policy. Investors who value sustainability, but do not wish to make investment decisions themselves, often choose socially responsible (SR) mutual funds. These investors in particular put their trust in managers of SR mutual funds to act responsibly as well as to make forward-looking and sustainable investment decisions. Thus an additional evaluation concerning CSI criteria is not only interesting from an investor's point of view but should be of particular importance for SR mutual funds.

Dorfleitner et al. (2020) examine the relationship between corporate social performance (CSP) and corporate financial performane (CFP) regarding ESG (which stands for environmental, social and governance) rating as well as the *Thomson Reuters Controversies Score*[1] within the context of portfolio selection. By collecting and evaluating negative media stories from global media sources, this controversies score offers a new dimension with which to measure ESG-based scandals caused by the corporate behavior of the company under consideration.

In this study, we not only examine the ESG and controversies persistence of US mutual equity funds as a new dimension of ESG and a measurement for CSI, but also provide an assessment of this social performance (SP) for investors. This paper is the first to analyze and evaluate the persistence of US mutual equity funds regarding CSI as measured by an (ESG) controversies score based on an evaluation of the respective companies in their historical stock holdings.

Naturally, an important question with theoretical and practical consequences is whether SRI involves a direct performance benefit for investors. Concerning the academic literature, controversial results can be observed. While some authors show an outperformance of investors who apply socially responsible screens methods on their portfolios (see Kempf and Osthoff (2007), Edmans (2011)), others ascertain neither performance benefits (Statman

[1]The scores are currently published by Refinitiv.

and Glushkov (2009)) nor negative performance (Hong and Kacperczyk (2009)).

Among SRI strategies some authors investigate the influence of positive or negative ESG based events and investors' reactions (Krüger (2015)) or the influence of bad media on firm value (Lundgren and Olsson (2009)).

In addition to the evaluation of individual companies based on ESG criteria, the importance of so-called sustainable funds is steadily increasing. According to the Report on US Sustainable, Responsible and Impact Investing Trends (see US SIF Foundation (2018)) the AUM of SRI assets is $ 12.0 trillion in the US market only.

Consequently, another major field of the SRI literature deals with the financial performance of SR mutual funds compared with conventional mutual funds. However, the majority of authors reports that no performance differences are achieved here (see, i.e., Statman (2000), Bello (2005), Bauer et al. (2005), Cortez et al. (2008), Utz and Wimmer (2014)). Furthermore various other authors investigate financial performance persistence of mutual funds (Hendricks et al. (1993), Carhart (1997), Muñoz et al. (2013)). In summary, hitherto no significant sustained overperformance of fund managers has been demonstrated in these studies either.

By analysing the ESG performance of mutual funds, Wimmer (2013) finds that the overall ESG rating based SP of SR mutual funds is persistent only for a short period and decreases after several years. Thus, in particular, ethically motivated value-driven investors must be attentive when selecting SR mutual funds to ensure that their requirements for sustainability are maintained in the medium and long-term. While there may be varying reasons for this group to invest in SR funds, Barreda-Tarrazona et al. (2011) show that investors who place a high value on sustainability also invest significantly more in SR funds once they are informed and convinced of their SR nature, even if they expect a lower return compared with a non-SR alternative.

This study is specifically aimed at investors who are primarily interested in responsible and sustainable investment criteria (Bollen (2007), Renneboog et al. (2008)) as opposed to performance-optimized portfolios. Since corporate social responsibility (CSR) criteria of companies are measured and quantified by ESG scores, we measure the ESG scoring of an SR mutual fund holding by weighting the ESG-scores of the individual assets. In the same way, we measure the controversies scoring of an SR mutual fund. To the best of our knowledge, we are the first to investigate the controversies score persistence of mutual funds by using a score based on ESG media scandals.

In this paper, we demonstrate that the short and long-term CSI and ESG persistence of SR mutual funds are preserved. Moreover, we show that the controversies-based SP of high-paid managers surpasses that of the lower-paid managers, whereas their ESG-based SP is clearly worse.

Finally, it becomes evident that funds with a very high ESG rating tend to have low controversies ratings and vice versa. From an ethical investor's point of view, it becomes apparent that they have to choose one side in their investment decisions.

Our work is organized as follows: In Section 2 we discuss our data set and introduce the methodology. The results are presented and discussed in Section 6.3. The Section 6.4 concludes this paper.

## 6.2 Data and methodology

To create our database we commence with a list of sustainable and responsible and impact mutual funds from the US SIF website, which provides a sample of all SRI classified mutual funds in the United States (https://charts.ussif.org/mfpc/). Since the current version of this website only covers open funds, we also include closed mutual funds, collected from former US SIF mutual funds lists, to prevent our results from survivorship bias. Next, we connect this list to the 'CRSP Survivor-Bias-Free US Mutual Fund Database', which contains various information, such as the exact holdings of the respective funds on previous reporting dates from 2003-2018. Furthermore, we add following two ESG based scores for the individual funds' compositions.

As the world's largest ESG rating database, we choose Thomson Reuters ESG score, which evaluates a company's environmental, social, and governance performance. It is calculated with the use of ten main themes (including resource use, innovation, emissions, human rights, workforce, management) based on publicly available company-reported data. These categories receive an individually measured category score and are weighted in the associated ESG pillar score. The aggregated pillar scores result in the overall ESG score, which is ranked by percentile and benchmarked against the industry (for more details regarding calculation see Refinitiv (2022)). In addition, we use the *Thomson Reuters Controversies Score*. As Thomson Reuters' latest scoring methodology, this score investigates firm controversies and adds a new dimension to previous approaches by capturing negative media stories from global media sources. In addition, it is benchmarked on respective industry groups (see Refinitiv (2022)).

Both scores range from zero to one hundred, and are interpreted in such a way that the higher the score the better the respective ESG or controversies rating. Table 6.1 shows the descriptive statistics of our data set.

To measure the overall ESG and controversies score of a fund on a particular reporting date, we weight the latest available scores before the reporting date concerning the individual securities weightings of the fund's composition. This calculation follows Dorfleitner et al. (2012) regarding the social return $S_P$ of portfolio holding, which satisfies the portfolio

Table 6.1: Descriptive statistics

| Score | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| ESG Score | 422 | 53.5477 | 10.0938 | 27.2809 | 77.3793 |
| Controversies Score | 422 | 74.3090 | 13.2898 | 37.2108 | 100.0000 |

This table presents the mean, standard deviation, minimum and maximum values of the TR, controversies of the full dataset.

additivity property

$$S_P = \sum_{i=1}^{N} x_i \cdot S_i,$$

where $\vec{x} = (x_1, \ldots, x_N)^T$ represents the portfolio weights of the assets with $\sum_{i=1}^{N} x_i = 1$.

Although both scores are available for an average of 2000 securities, we only take equity funds into account for which more than 60 percent[2] of the fund's holding is covered by both scores[3]. Thus we obtain a database of over 60 different funds and over 400 fund compositions[4] with ESG and controversies score coverage. The number of fund compositions per year is displayed in Table 6.2.

Table 6.2: Number of fund compositions per year

| Year | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---|---|---|---|---|---|---|---|---|
| N | 10 | 12 | 14 | 21 | 35 | 28 | 27 | 25 |
| Year | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
| N | 25 | 27 | 28 | 26 | 37 | 36 | 36 | 35 |

This table reports the number of fund compositions per year of our dataset.

The possible problem of overlapping stock holdings of individual funds is no issue in our sample, as can be seen from the wide variety of observed portfolio scores.

Following a similar approach to Wimmer (2013), we categorize the funds concerning their overall ESG and controversies score on a yearly basis. For this purpose we construct four equally weighted portfolios for each score, one for each quartile of the funds ratings on a

[2]As a robustness test, we examine various percentages (50 %, 70%). The results remain materially unchanged.

[3]As another robustness test, we calculated our portfolios with all available ESG or controversies ratings. Again, the results remain materially unchanged.

[4]The number of available fund compositions increases from about 10 in earlier years to about 35 in later years. Over 83% of the funds exhibit at least 3 consecutive observations. On average, our data base covers 6 observations per fund.

yearly basis. This yields to eight portfolios, four built on ESG scores and another four built on controversies scores. Here, ESG portfolio 1 contains the quarter of all funds with the lowest ESG score, while controversies portfolio 1 contains the 25 percent of all funds with the lowest controversies score. Analogously ESG/controversies portfolio 4 contains the 25 percent of all funds with the respective best overall score.

## 6.3 Results and discussion

The presented results are sorted according to their time horizon, which reflects possible investment horizons. Following Wimmer (2013), we define short-term as being one year, mid-term horizon as being one to three years and long-term as three years or more.

### 6.3.1 Short-term persistence

To examine the short-term persistence of mutual funds, we examine a contingency table of current and subsequent one-year ranking transition. Table 6.3 presents the probability of a fund in a specific ESG or controversies rank portfolio of falling in each rank portfolio in the subsequent year. The data shows that for a one-year persistence, the funds' ESG and controversies score remains largely unchanged, especially for portfolios 1 and 4 of each score. Thus the highest probabilities of remaining in the top quartile are observed for funds in the top quartile (approximately 79% for ESG and 73 % controversies portfolios) as well as for funds in the bottom quartile of remaining in the bottom quartile (approximately 85% for ESG and 73% for controversies portfolios).

Table 6.3: Contingency table of controversies and ESG portfolios.

| Score | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Controversies | 1 | 0.7333 | 0.2111 | 0.0555 | 0.0000 |
| | 2 | 0.2841 | 0.4204 | 0.2841 | 0.0114 |
| | 3 | 0.0919 | 0.3563 | 0.4023 | 0.1494 |
| | 4 | 0.0109 | 0.0652 | 0.1956 | 0.7283 |
| ESG | 1 | 0.8469 | 0.1122 | 0.0408 | 0.0000 |
| | 2 | 0.0330 | 0.6374 | 0.2637 | 0.0659 |
| | 3 | 0.0000 | 0.1363 | 0.5454 | 0.3182 |
| | 4 | 0.0125 | 0.0125 | 0.1825 | 0.7875 |

This table displays the contingency table of initial and subsequent fund controversies and ESG quartile rank rating. In every year between 2003 and 2018, the observed funds are ranked in one of the four rank portfolios. These rankings are connected to the subsequent fund quartile ranking.

All things considered, additionally to the findings of Wimmer (2013) for the ESG rating of mutual funds, we have an indication that “winners stay winners" and “losers stay losers" also applies to the controversies score.

Considering the Spearman correlation test for ESG and controversies scores of the portfolios we measure a significant non-zero correlation between the original and subsequent ranking.

### 6.3.2 Mid- and long-term persistence

From the perspective of an investor it is of course interesting to find out how far the ESG and controversies scoring of SR mutual funds persist throughout the following years. For this purpose, we calculate the average scores of the eight portfolios in their initial year as well as for the subsequent four years, whilst refraining from any rebalancing. Again, portfolio 4 contains the top quartile funds with the highest ESG and controversies scores and portfolio 1 contains the bottom quartile funds with the respective lowest ratings.

Figures 6.1 and 6.2 show the descriptive data for the development of the four ESG and controversies portfolios in the subsequent four years. When considering the controversies portfolios it becomes evident that the top portfolio remains by far the best portfolio in the following years. The other three portfolios show no major changes in their score developments and thus maintain their ranks.

By regrading the ESG portfolios, it can be seen that the portfolios 2 to 4 converge with regard to their overall ESG scores. Even with a split into two sub-periods (2003 to 2010, 2011-2018), the effect described above remains intact. However, in contrast to Wimmer (2013) we cannot find a change in the rank formation of the ESG portfolios when considering the Thomson Reuters ESG score.

Again, when considering the Spearman correlation test for ESG and controversies rank portfolios, we measure a significant non-zero correlation between the original and each of the subsequent four rankings.

### 6.3.3 ESG and controversies scores vs. Management Fee

Chevalier and Ellison (1999) show that the performances of mutual funds are related to the characteristic of fund managers, such as behavioral differences, age, and education. However, especially for mutual funds, not only the financial performance is important, but also the quality of the investment decisions with regard to various sustainability criteria. In particular, it is value-driven ethical investors who demand the highest possible standards, which poses a behavioral challenge for managers, especially since financial performance must not be completely neglected, in order to remain competitive. For instance, Dorfleitner et al. (2020) show that particularly small companies with low ESG ratings achieve significant overperformance. Thus it remains questionable whether managers

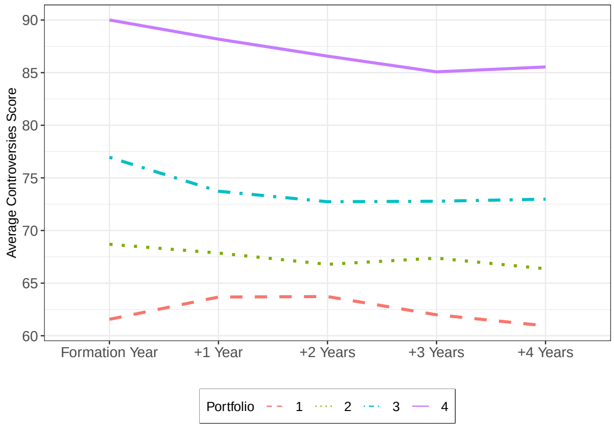



Figure 6.1: Long-term persistence of controversies portfolios.

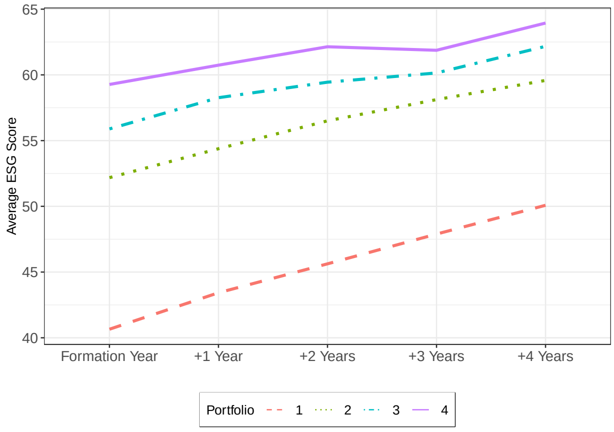



Figure 6.2: Long-term persistence of ESG portfolios.

Description: For the years from 2003-2018 we rank each fund into equal-weighted quartile portfolios based on their overall ESG scores as well as in equal-weighted quartile portfolios based on their overall controversies scores. The lines represent the ESG and controversies score of the four rank portfolios in their formation years and the subsequent four years without any changes to their formation. Funds that initially achieve the highest ESG or controversies ratings are contained in portfolio 4 and those with the lowest ratings appear in portfolio 1.

avoid investment opportunities despite an attractive performance in order to achieve a high ESG standard.

To investigate whether high-paid managers of SR mutual funds demonstrate better ESG or controversies social performances of their funds than the lower priced ones, we add the respective fund management fee[5] of over 300 different funds to our dataset. The descriptive statistics of the additional dataset are shown in Table 6.4.

Again, we divide our portfolios into eight rank portfolios (four for each score). Portfolio 1 includes the funds with the 25% low priced managers whereas portfolio 4 covers the 25% of high-paid managers. Afterwards we calculate the overall ESG and controversies scores

[5]Note that the management fee does not include the expense ratio.

Table 6.4: Descriptive statistics

| | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Management Fee | 306 | 0.5675 | 0.2062 | 0.05 | 1.00 |

This table presents the mean, standard deviation, minimum, and maximum value (in %) of the management fee dataset.

of the respective portfolios. Note that due to the data limitation, sufficient observations (minimum two for each rank portfolio) are only available as from 2007. Similar to the procedure above, we examine the initial scores as well as the developement over the ensuing years.

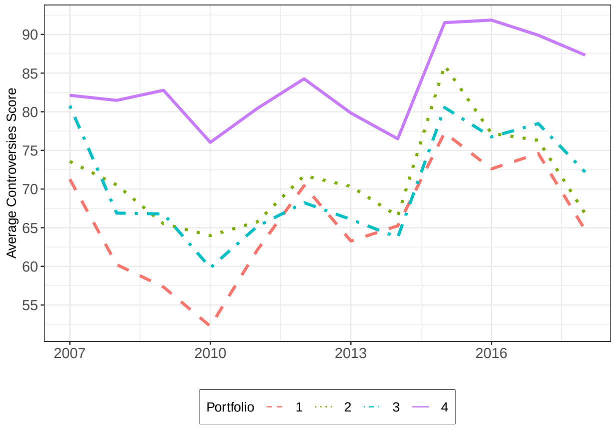



Figure 6.3: Controversies score of fee portfolios.

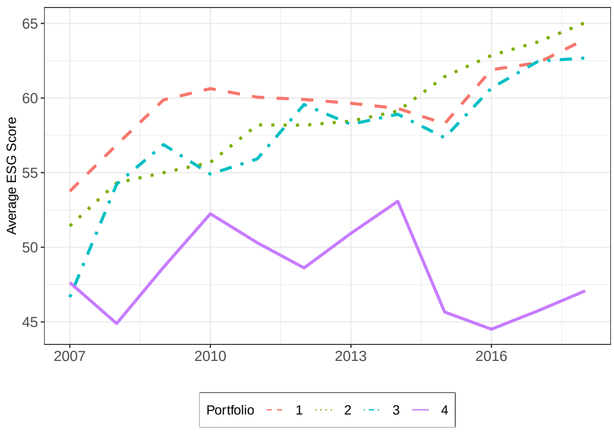



Figure 6.4: ESG score of fee portfolios.

Description: In the years from 2003-2018 we rank each fund in equal-weighted quartile portfolios based on their management fee. The lines represent the ESG and controversies score of the four rank portfolios from 2003-2018. Funds that are managed by the highest-paid managers are contained in portfolio 4 and those which are managed by the lowest-paid managers are contained in portfolio 1.

By considering Figures 6.3 and 6.4 we can see some noteworthy results: On the one hand, the highest paid managers show the best ongoing controversies scoring, whereas the scores of the other three portfolios from 2014 onwards no longer exhibit any major differences.

On the other hand, this effect changes dramatically when considering the ESG scoring of the rank portfolios. Here, the highest paid managers show by far the lowest ESG score. Surprisingly, in the majority of years, the highest overall ESG scoring can be detected by the lowest paid managers. After 2015, there are again no major differences within the rank portfolios 1 to 3.

Note that some of the results in early years are driven by few funds per portfolio due to the limited sample size.

### 6.3.4 ESG score vs. controversies score

Another interesting question for investors is whether SR mutual funds with high ESG ratings also achieve high controversies scores and vice versa.

For this purpose we begin with the four ESG rank portfolios and calculate the respective controversies ranking and vice versa. Again we examine the developement of the subsequent four years. Concerning Figures 6.5 and 6.6, we surprisingly detect a major change in the ranks of the respective portfolios. Conversely, the best ESG rank portfolio exhibits one of the worst controversies scores and, on the other hand, the worst ESG rank portfolio shows by far the best ongoing controversies scores. A similar picture can be seen when considering the ESG scoring of the controversies rank portfolios. Once more, the best controversies rank portfolio shows the worst ESG scoring. One reason for this development is the generally rather negative correlation of ESG and controversies score (see Dorfleitner et al. (2020)). It is therefore difficult for fund managers to be leaders in both ratings. Another possible explanation could be that they maintain their investment policies concerning the focus on either ESG or controversies ratings. We leave a clarification of this matter to further research.

## 6.4 Discussion and conclusion

First, the results shown above can be considered as good news for value-driven investors. With the growing popularity of ESG ratings, SR funds are obviously also pursuing clear and relatively consistent investment policies. From the data it becomes apparent that this effect can be seen for both ESG and controversies portfolios, not only in the short term but also in the medium and long term. This is particularly useful for investors who do not wish to actively rebalance their investments.

Second, the question arises as to why particularly high-paid fund managers perform well in

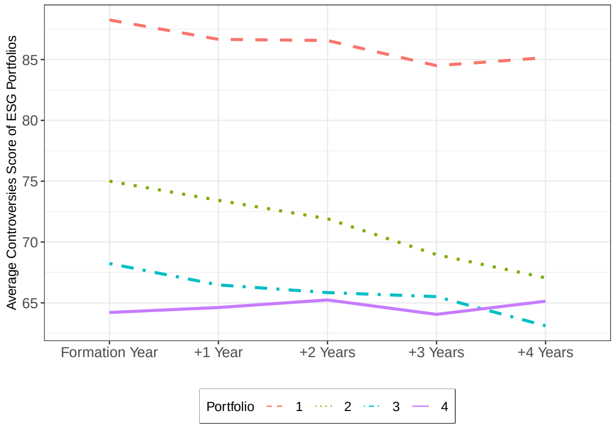



Figure 6.5: Controversies Scoring of ESG rank portfolios.

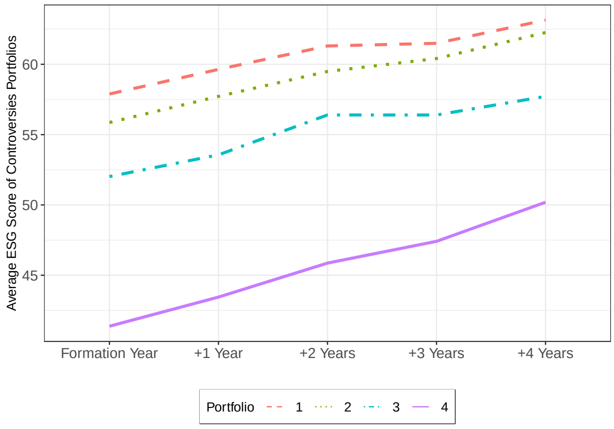



Figure 6.6: ESG Scoring of controversies rank portfolios.

Description: In the years from 2003-2018 we rank each fund in equal-weighted quartile portfolios based on their overall ESG scores as well as in equal-weighted quartile portfolios based on their overall controversies scores. The lines represent the ESG or controversies score of the four controversies, respectively ESG rank portfolios in their formation year and the subsequent four years without any changes to their formation. Funds that initially achieve the highest ESG or controversies ratings are contained in portfolio 4 and those with the lowest ratings are contained in portfolio 1.

controversies ratings but worse in the ESG rating of their funds than lower-paid managers. On the one hand, media attention and influence is more present than ESG reporting and ratings. Thus, particularly high-paid managers may try to avoid negative reporting upon the companies in which they invest. On the other hand, this may also prevent sudden performance losses due to media scandals. Therefore, high-paid managers try to avoid companies that are prone to scandals by placing special emphasis on companies that exhibit good controversies SP compared with the remainder of their respective industry groups. Nevertheless, a certain level of profitability of the investments needs to be reconciled with sustainability considerations.

Third, it becomes apparent that there are difficulties for SR funds to become leaders in both ESG and controversies. These results are not surprising and remind us of the “the higher you fly the harder you fall" hypothesis (Dorfleitner et al. 2020). Especially here, investors must decide to what extent one or the other rating is more important to them and to find a personal preference.

All in all, our results show that there are certain similarities but also differences between the ESG and the controversies rankings of mutual funds. The results can be summarized and delimited as follows:

In the short-term development almost no differences can be seen when comparing the initial and subsequent portfolio rankings of both controversies and ESG scoring. Also, in the longer-term (Section 6.3.2), many ESG portfolios are virtually identical or almost converge in their ESG scores. The respective controversies portfolios show a rather delimited and constant development, especially in the top quartile, but the rankings also remain unchanged.

When we examine the relationship between ESG and controversies scores and management fees (Section 6.3.3), we find that higher-paid managers achieve better results regarding controversies scorings but worse results regarding ESG scoring. Again, the effect is particularly evident in the top quartile, whereas the other quartiles converge over time.

Last but not least, we find evidence of the fact that the controversies and ESG scores of mutual funds show clearly opposing developments. Funds with high ESG ratings tend to have comparatively low controversies ratings and vice versa.

Despite various robustness tests, the results of this first study are somewhat limited due to the limited sample size. Note, that in particular in the early years (2003-2005), some of the rank portfolios consist only of few funds. Therefore this may affect some of the early stage observations, but this effect disappears after only a few years. This work is intended to provide a first step toward examining CSI of SR equity funds and naturally leaves some space for further research based on a larger data basis.

If a value-driven investor considers the controversies component in addition to ESG criteria, certain investment decisions become more difficult.

Scandals, in particular, are difficult to predict, occur across all industries, and may have an enormous financial impact in the short- or even mid-term (see e.g. emission scandal, oil spill scandal, accounting scandal).

Ratings such as controversies scores help investors to assess companies regarding their vulnerability to controversies relative to companies in the same industry. Especially investors who value both ESG and controversies, find themselves to be in some degree of conflict. Our work provides the first step towards a new aspect of ESG assessment, leaving space for further investigative research.

## Acknowledgements

We would like to thank Dr. Maximilian Wimmer for useful discussions and support.

# Chapter 7

# The Corporate Payout Puzzle: About the Payout Policy between CSI and CSR

This is based on the joint work with Christian Sparrer (University of Regensburg) and is currently under review from the *European Journal of Finance*.

**Abstract** An international sample with 7,260 firms from 2003 to 2021 offers new insights relating corporate social irresponsibility (CSI) and responsibility (CSR) to corporate payout. We provide robust evidence that irresponsible firms (i.e., firms with CSR-related scandals) reduce their payout and prefer to cut stock repurchases rather than dividends, while firms with high CSR performance pay higher dividends. Moreover, a pair-matched sample shows that irresponsible firms take more time to announce the next repurchase. Overall, our results provide further challenging implications for the equity market timing hypothesis and suggest that corporate payout serves to control agency problems of CSR.

**Keywords** payout policy, dividends, share repurchases, corporate scandals, corporate social responsibility, ESG, agency theory, market timing

**JEL** G35, M14

## 7.1 Introduction

The payout policy of firms is one of the most important interactions between executives and shareholders, and it remains a major question in corporate finance and accounting literature (see e.g., Guttman et al., 2010; Deshmukh et al., 2013; Koo et al., 2017; Cejnek et al., 2021; Faulkner and García-Feijóo, 2022). While the theoretical and empirical literature has extensively examined corporate payout policy since the groundbreaking work of Lintner (1956) or Miller and Modigliani (1961), contemporary research increasingly considers the integration of non-financial information, such as corporate social responsibility (CSR) disclosures, in understanding a firm's financial decision-making process. Although CSR disclosure provides valuable insights into a firm's voluntary commitment to addressing environmental and social challenges, firms simultaneously try to conceal their unethical business practices. These practices, often referred to as corporate social irresponsibility (CSI), not only represent a theoretically distinct concept from CSR (see e.g., Ioannou and Serafeim, 2015; Bear et al., 2010) but can also have far-reaching implications on a firm's payout decision and ability to distribute financial resources via payout. On the one hand, firms may increase their stock repurchases in response to the market's overreaction to the scandal and buy back shares at a relatively low price. Simultaneously, scandals usually affect stakeholders' perception of the firm (Grappi et al., 2013). Customers may boycott the firm's products, and investors or capital lenders may refrain from supplying the firm with additional capital, limiting the company's financial resources available for payout. However, little attention has been paid to the interaction of CSI with corporate payout. In light of this academic void, this paper extends the understanding of corporate payout policies and provides new insights into the link between corporate social (ir-)responsibility and a firm's payout channels.

Our results provide robust statistical evidence for a negative relation between CSI and a firm's dividend payout and stock repurchases. To further test this relation, we use a hand-collected data set and propensity score matching to implement a time-to-event analysis. For a sample of pair-matched firms, we find robust evidence that being involved in a scandal is positively related to the number of days until the announcement of a stock repurchase. These results contrast with the equity market timing theory, as managers could miss the opportunity to buy back stocks at a relatively low price after a corporate scandal became public. Instead, in line with the precautionary cash holding theory, companies temporally reduce their payout activities in the aftermath of a scandal and may prefer to retain their cash flows to secure future investments.

In addition, our results show that firms with high CSR ratings are more likely to pay dividends and distribute more financial resources via their payout channels.[1] These results

[1]We acknowledge the justified criticism regarding the black-box nature and rewriting of CSR ratings

remain robust for a 2SLS approach, which alleviates the potential concerns about the endogeneity of CSR ratings. Consistent with the agency problem of free cash flow, this supports the view that corporate payout policy helps to constrain managers' opportunistic incentives to extract non-financial rents through overinvestments in CSR.

Since Miller and Modigliani (1961), a vast majority of theoretical and empirical literature examines corporate payout policies. While a firm's payout policy often focuses on maximizing shareholder welfare, companies increasingly consider objectives beyond profit maximization, such as investments in environment-friendly production and supply chains, sound diversity policy, fair working conditions, and even charitable donations to local communities. These business activities, which are often summarized as corporate social responsibility (CSR), seek to enhance other stakeholders' welfare (Liang and Renneboog, 2017) and represent a firm's voluntary efforts beyond legal and regulatory requirements (see e.g., McWilliams and Siegel, 2001) to address the externalities it causes during its endeavor for profit maximization (Tirole, 2001). Some authors assert that CSR has to be accompanied by a tradeoff between shareholder value maximization and stakeholder welfare orientation (see e.g., Bénabou and Tirole, 2010; Masulis and Reza, 2015), while others postulate the coexistence or even compatibility of these two concepts (see e.g., Liang and Renneboog, 2017; Ferrell et al., 2016; Edmans, 2011).

As companies increasingly incorporate environmental and social aspects into their decision-making process, they have incentives to communicate these efforts through their CSR disclosure. Shareholders place increasing emphasis on the disclosure of non-financial information (Dhaliwal et al., 2011; Cahan et al., 2016; De Villiers et al., 2023) and integrate CSR information in their investment decisions (Christensen et al., 2022; Hartzmark and Sussman, 2019; Amel-Zadeh and Serafeim, 2018; Holm and Rikhardsson, 2008).

Still, unethical business practices, such as excessive environmental pollution, poor working conditions, bribery, or accounting fraud, have not simply vanished and are still lacking academic and societal attention. Corporate social irresponsibility (CSI), which is defined as unethical corporate behavior (and its measurement as a publicly disclosed corporate scandal), contrasts a firm's stakeholder welfare orientation but is not mutually exclusive to CSR (Aouadi and Marsat, 2018). Companies may be publicly perceived as sustainable and achieve high CSR ratings but can simultaneously be involved in scandals.[2] Motivated by the insurance-like protection derived from a high CSR reputation (see e.g., Godfrey, 2005; Bénabou and Tirole, 2010), these firms may feel less pressure to behave ethically because they face fewer sanctions for unethical business practices (Dorfleitner et al., 2022). On the

(see e.g., Berg et al., 2020). However, these concerns arise primarily in the context of portfolio construction and stock selection based on cut-off values or percentiles of CSR ratings. Since none of these applications are used in this study, we are not affected by selection bias in this respect.

[2]Section 7.3.4 discusses the correlation between CSR and CSI and provides anecdotal evidence of well-known corporate scandals to support this reasoning.

other hand, firms may use CSR in the aftermath of a scandal to regain public trust or to distract public attention and obscure other unethical practices. Additionally, CSR ratings often utilize company-reported data, and companies may be able to favorably distort these ratings by selective disclosure (Christensen et al., 2022; Drempetic et al., 2019). Therefore, a sole focus on CSR disclosure or CSR ratings leads to a misperception of a company's ethical orientation, and researchers need to view CSR and CSI as two separate concepts (Ioannou and Serafeim, 2015; Bear et al., 2010).

Despite the rich literature on corporate payout, research on the relationship between CSI and CSR with the firm's payout policy is still rare. Sung et al. (2006) examine how changes in dividends following a corporate scandal impact abnormal returns. By applying an event study methodology to a sample of 22 corporate scandals, they find positive abnormal returns for firms that increase payout after they have been involved in a scandal. Benlemlih (2019) show that US firms with high CSR ratings pay more dividends, and their dividend payments are more stable over time. For a sample of US firms, Cheung et al. (2018) conclude that the propensity to pay dividends is not directly affected by the level of CSR but that CSR influences the amount of dividends paid. Samet and Jarboui (2017) examine how CSR is linked to dividends and stock repurchases within the European market. For companies listed in the EUROSTOXX 600, the authors find that firms with high CSR performance tend to prefer repurchases over dividend payments.

We contribute to the literature in various ways. First, to the best of our knowledge, literature focused on the direct link between CSI with corporate payout is still completely missing. Corporate scandals can have far-reaching effects on the firm and substantially impact the company's payout decisions. While Sung et al. (2006) focuses on the impact on stock returns, our paper fills the academic gap and examines how patterns of irresponsible corporate behavior are linked to the firm's payout decisions. Moreover, compared to existing literature, we provide a more holistic picture of how CSR and corporate payout are linked in a global setting. Contrasting existing literature, we do not rely on a single payout channel or financial market. Instead, we examine both instruments (dividend payment and stock repurchases) in the context of CSR as well as CSI simultaneously within an international sample over an extensive period from 2003 to 2021. In addition to the financial resources spent on dividends or repurchases, we also explore the linkage of CSR and CSI with the propensity to pay dividends (i.e., payer/non-payer) and to repurchase stocks (repurchaser/non-repurchaser). Finally, we implement a 2SLS regression to address potential concerns about the endogeneity of CSR ratings within the context of corporate payout and employ two empirical tests to ensure the validity of our theoretical reasonings (the agency problem of free cash flow and the precautionary cash holding theory) underlying our results.

The paper proceeds as follows: In section 7.2, we develop our theoretical reasoning on how

CSR and CSI might be linked with corporate payout decisions. Section 7.3 describes our data and reports descriptive statistics. Section 7.4 discusses our results, addresses potential limitations by using alternative measures for CSR and CSI, and implements two empirical tests to further verify our results. Finally, Section 7.5 concludes the study.

## 7.2 Theoretical Development

The predominant stream within the literature on corporate payout seeks to identify different drivers of dividend payouts (see e.g., La Porta et al., 2000; Fama and French, 2001; Baker and Wurgler, 2004; DeAngelo et al., 2006; Denis and Osobov, 2008; Von Eije and Megginson, 2008), or focuses on the stickiness and smoothing of dividends over time (see e.g., Lintner, 1956; Guttman et al., 2010; Lambrecht and Myers, 2012; Leary and Michaely, 2011; Larkin et al., 2017; Brockman et al., 2022).

Other studies discuss the recent shift in corporate payout policies from dividends to repurchases as the preferred form of payout (see e.g., Jagannathan et al., 2000; Fama and French, 2001; Grullon and Michaely, 2002; Skinner, 2008; Von Eije and Megginson, 2008), although dividends remain an essential proportion of the total payout (Renneboog and Trojanowski, 2011). Another strand of literature (see e.g., Dittmar and Field, 2015; Ben-Rephael et al., 2014; Ikenberry et al., 2000; Peyer and Vermaelen, 2009) investigates a firm's preference for stock repurchases in the context of equity market timing (i.e., a well-timed stock repurchase) or how equity market timing impacts shareholder value (Babenko et al., 2020).

Brav et al. (2005) and Graham and Harvey (2001) use survey evidence to conduct insights into the managerial motives for stock repurchases. Von Eije and Megginson (2008) highlight the relation of various firm characteristics with stock repurchases. De Cesari and Ozkan (2015), Ferri and Li (2020), and Faulkner and García-Feijóo (2022) examine how executive payment incentives or a CEO's past corporate experience impacts the decision-making process in corporate payout policies. Farre-Mensa et al. (2021) provide empirical evidence that US firms often fund their payout with the issuance of new capital during the same year. Massa et al. (2007) show that companies are pressured to mimic the repurchase behavior of their competitors within the same industry. Finally, a strand of literature emerged that studies payout policy during extreme economic turmoils, such as the 2008/09 financial crisis (Bliss et al., 2015) or the COVID-19 pandemic (Cejnek et al., 2021; Ntantamis and Zhou, 2022).

### 7.2.1 Payout policy in the context of CSR

This section draws upon two major theoretical branches, agency theory and signaling theory, to discuss potential relations between CSR and a company's payout policy.

First, following the *agency theory* of Jensen (1986), firms with abundant financial resources may face severe agency problems (Servaes and Tamayo, 2014). These problems can manifest themselves in the form of managerial decisions driven by the incentive to divert free financial resources to their own advantage (Stulz, 1990; La Porta et al., 2000; Ferrell et al., 2016) rather than following the objective to maximize shareholder value. In anticipation of managerial opportunism, shareholders demand dividends, or the firm will use stock repurchase programs as a disciplinary mechanism (Easterbrook, 1984; De Cesari and Ozkan, 2015) and to restrict agency conflicts (DeAngelo et al., 2006; Lambrecht and Myers, 2012; Farre-Mensa et al., 2014).[3]

In the context of CSR, Barnea and Rubin (2010) and Brown et al. (2006) argue that managers who invest in CSR establish a personal ethical reputation from which they can derive private benefits, such as building a network, receiving gifts, or entrenching themselves within the firm. Managers may be tempted to invest in CSR beyond the optimal level from a firm's perspective. Any investments surpassing this equilibrium level do not generate additional direct value for the firm (Godfrey, 2005; Ye and Zhang, 2011) or may even lower short-term financial performance (Lopatta et al., 2022) but still provide private benefits for the managers.[4] Thus, several researchers assert that overinvestments in CSR illustrate a manifestation of managerial agency problems and empire-building (Bénabou and Tirole, 2010; Krüger, 2015; Cheng et al., 2014b) and that these CSR activities represent a non-financial and more subtle form of managerial rent extraction at the expense of shareholder value (Masulis and Reza, 2015).

Again, in anticipation of managers' incentives to overinvest in CSR, companies with an already good CSR reputation can use dividend payout or stock repurchases as a disciplinary mechanism to reduce agency problems and to better align the interests of shareholders and stakeholders. Consequently, we would expect a positive relationship between CSR and the firm's payout.

The second view draws upon arguments of the *signaling theory* (Bhattacharya, 1979; Miller

[3] DeAngelo et al. (2006) highlight the importance of distributing free cash flows to prevent agency problems. They show that if well-established firms had retained their free cash flows over a long period, they would have an enormous cash balance and be almost entirely independent from external financing. Consequently, the capital market would lose its ability to monitor managers' behavior, and paying dividends or repurchasing stocks is an important mechanism to limit managerial opportunism.

[4] Bénabou and Tirole (2010) describes these agency problems as a zero-sum game in which if everybody engages in CSR, no one is rewarded for it. Because a manager's ability to achieve private benefits also depends on the level of CSR commitment from his surrounding, managers have further incentives to overinvest.

and Rock, 1985; John and Williams, 1985). In general, there are information asymmetries between managers and external stakeholders because managers have private information about the current and future cash flows of the firm. To counteract these frictions, managers often voluntarily provide additional information (Healy and Palepu, 2001). According to the signaling theory, firms can use dividend payouts or stock repurchases to reduce information asymmetries and directly signal private information and thereby the “true” value of the company to the market (see e.g., DeAngelo et al., 2006, Lambrecht and Myers, 2012, Guttman et al., 2010). Consequently, managers are more likely to increase dividend payout or to initiate stock repurchases when the opinions of the capital market and managers diverge on the true value of the company (Lie, 2005).

However, instead of increasing dividends or initiating repurchases, firms can use other instruments to credibly disclose (private) CSR-related information and reduce information asymmetries about how the company will deal with future CSR-related challenges. Companies with superior CSR performance often use extensive sustainability reports or CSR ratings to transparently disclose information about their alignment with sustainable goals (see e.g., Dhaliwal et al., 2011; Cheng et al., 2014a). It follows that firms with good CSR ratings would benefit less from the signaling mechanism of payout. In turn, if a firm uses its payout channels primarily to signal information about the company’s ability to deal with future CSR-related challenges, we would expect firms with low CSR ratings to pay more dividends or increase their stock repurchases.

### 7.2.2 On the link between CSI and corporate payout

Similar to the previous section, we employ two prevalent theories (market timing hypothesis and precautionary cash holding theory) to explore the link between CSI and corporate payout.

First, following the *market timing hypothesis*, firms are expected to choose the optimal timing for their stock repurchase. Brav et al. (2005) and Graham and Harvey (2001) emphasize the importance of undervaluation due to information asymmetries as a key consideration in the process of stock repurchases. Managers use this pricing uncertainty and buy back shares at a relatively low price (see e.g, Peyer and Vermaelen, 2009; Baker et al., 2002; Ikenberry et al., 2000; Brav et al., 2005; Ben-Rephael et al., 2014; Jagannathan et al., 2000). Simultaneously this signals the “true” value of the company to the market.[5]

[5] One might argue that managers can signal their material, nonpublic information with the *announcement* of a stock repurchase. However, there are two essential prerequisites for this mechanism: (1) the assurance of the credibility of the signal and (2) a mechanism to eliminate incentives for false signaling (for example, costs for false signaling). While the timing of share repurchase announcements can be chosen flexibly and thus are generally considered credible, the sole announcement does not obligate the firm to repurchase shares (Lie, 2005). In the absence of costs for false signaling, share repurchase announcements fail the second requirement, which is in line with the findings of Grullon and Michaely (2004). Investors are generally more

While CSR ratings help reduce information asymmetries, corporate scandals, on the other hand, create uncertainties about the consequences of the scandal and the company's ethical orientation and future value (see e.g., Bowen et al., 2008; Dhaliwal et al., 2011; El Ghoul et al., 2011; Robinson et al., 2011; Goss and Roberts, 2011; Sharfman and Fernando, 2008; Ye and Zhang, 2011). When share prices have fallen due to a scandal and managers disagree with the market's pricing of information surrounding the scandal, they may take advantage of this pricing uncertainty and repurchase their shares. Thus, following the market timing hypothesis, managers are more likely to repurchase stocks after a scandal.

In contrast, the second view builds upon the assumption that the decision to pay dividends or to initiate stock repurchases also depends on the availability of sufficient free cash flows. Brav et al. (2005) highlight, that managers set investment policies before payout decisions. So, after a company has financed all net present value positive investments, it can distribute the financial slack via dividends or stock repurchases (Dittmar and Dittmar, 2008; Skinner, 2008). Nevertheless, firms may face various types of market frictions that limit their access to capital markets and their ability to finance all profitable and desired investments (i.e., the firm is financially constraint).[6] It follows that financially constrained firms prefer to use internal funds to finance their investments and in this case, the company most likely lacks further financial resources for payout (Bliss et al., 2015).

Within this view, corporate scandals are associated with an increase in uncertainty that can impose these market frictions onto the firm and hamper the ability to gain external financing in the future. In line with our reasoning, Goss and Roberts (2011) show that social irresponsible firms pay between 7 to 18 basis points more for bank loans. Besides the impaired access to external financing, customers may respond to the scandal with a boycott of the firm's products, further reducing free cash flow.

Based on the precautionary cash holding theory, firms anticipating an increase in these frictions will hoard cash as a buffer to deal with adverse shocks when external financing is costly (see e.g., Bates et al., 2009; Han and Qiu, 2007; Almeida et al., 2004; Bolton et al., 2013; Leary and Michaely, 2011).[7] Firms will be reluctant to distribute their financial slack through dividends or stock repurchases, and we would expect a negative relationship between CSI and corporate payout.[8]

concerned about a firm's commitment to the repurchase (Bonaimé et al., 2020) and thus, we mainly focus on the actual stock repurchase instead of the announcement thereof.

[6]These market frictions may include, for example, a high dependency on bank loans, the inability to issue new equity, or restrictive debt covenants that prevent the firm from borrowing new debt (see e.g., Lamont et al., 2001; Cheng et al., 2014a). For a more in-depth definition and discussion of financial constraints, see, for example, Farre-Mensa and Ljungqvist, 2016.

[7]This reasoning is consistent with Bliss et al. (2015). They show that firms reduce their payout in response to an increase in external financing costs and a sharp rise in overall uncertainty during the 2008/09 financial crisis. Within our setting, a corporate scandal causes uncertainty and can be seen as a negative shock to the availability of the firm's financing options, but instead of affecting the entire financial market (as in the case of the financial crisis), this effect is specific to the firm involved in the scandal.

[8]Note that cash hoarding after a scandal may be imposed on the company externally by governments,

## 7.3 Data & Summary Statistics

WWe obtain our data from mainly two sources. Financial statement data come from Compustat, with missing values for non-US firms filled with corresponding data from Thomson Reuters Datastream. CSR- and CSI-related data are drawn from Refinitiv. Share prices for US firms are derived from CRSP and for non-US firms from Thomson Reuters Datastream. In the following, we provide a brief overview of our variables, but a more detailed description can be found in table A.1 in the appendix.

### 7.3.1 Dependent variables

While dividends have received considerable attention in early academic discussions, stock repurchases have recently seen a sharp increase in popularity (Jagannathan et al., 2000; Fama and French, 2001; Grullon and Michaely, 2002; Brav et al., 2005; Skinner, 2008). These two payout channels are not used interchangeably or as substitutes (De Cesari and Ozkan, 2015) but serve as complementary forms of payout (Jagannathan et al., 2000; Grullon and Michaely, 2002). Firms deliberately decide on the right payout channel for their current situation. Since Lintner (1956), dividends are expected to grow smoothly over time and are generally viewed as a permanent and binding commitment. Hence, managers are reluctant to cut or forgo dividends altogether (Brav et al., 2005). Stock repurchases, however, are used as a flexible mechanism to distribute surplus of cash without any obligation to repeat (see e.g., Jagannathan et al., 2000; Guay and Harford, 2000; Grullon and Michaely, 2002; Brav et al., 2005; Von Eije and Megginson, 2008). A reduction in stock repurchases conveys different information than a change in dividends (Guttman et al., 2010) and firms are often expected to time their repurchases (Brav et al., 2005; Graham and Harvey, 2001), whereas dividend payments are expected to occur on a regular basis.

As a measure for the dividend channel, we follow literature (see e.g., Fenn and Liang, 2001; Denis and Osobov, 2008; Brav et al., 2005; Deshmukh et al., 2013) and use cash dividends on common stocks. We define $Div$ as the logarithm of 1 plus cash dividends on common stocks. Moreover, following Von Eije and Megginson (2008), Bhattacharya and Jacobsen (2016) and Denis and Osobov (2008), we use a dummy variable $D_{Div}$ to capture a firm's propensity to pay dividends, which equals one if the firm pays out cash dividends on common stocks (i.e., the firm is considered a dividend payer) and zero otherwise (i.e., non-payer).[9]

institutions, regulators, or courts and is not necessarily the company's own decision. Nevertheless, our argument remains unchanged because it is unaffected by the motivation for these cash savings.

[9] Our results remain unchanged if we employ the total amount of dividends paid (common plus preferred dividends) for $Div$ and $D_{Div}$.

Similarly, we employ a variable for the total amount of cash spent on stock repurchases (*Rep*), which is the logarithm of 1 plus the expenditures on the purchase of common and preferred stocks minus the change (first difference) in preferred stock reduction (Hong et al., 2012). In addition, following De Cesari and Ozkan (2015), we also include a dummy variable $D_{Rep}$, with a value set to one if the company has repurchased stocks in a given year (i.e., $Rep > 0$) and zero otherwise.

### 7.3.2 Measurement of CSR and CSI

We use Refinitiv's *ESG Score (ESG)* to quantify a firm's CSR performance. This score assesses the company's environmental, social, and corporate governance performance relative to the firm's industry peer group and assigns the company a score between 0 and 100. High values of the *ESG Score* indicate a superior corporate social performance relative to the firm's peer group.

However, as mentioned earlier, we are aware of the criticism regarding ESG scores and address potential concerns about the endogeneity of CSR ratings within a corporate payout context. Following El Ghoul et al. (2011), we use the two-digit SIC industry average ESG score (excluding the respective firm) as an exogenous instrument to derive an endogeneity-robust ESG score estimation ($ESG^{est}$) for each firm. In section 7.4.3, we discuss further prominent issues of ESG ratings and will alleviate some of them.

Following Dorfleitner et al. (2022), we measure CSI as publicly disclosed unethical corporate behavior (i.e., corporate scandals) regarding environmental, social, or corporate governance issues with the so-called Refinitiv *Controversies Score (CS)*.[10] Refinitiv captures publicly disclosed news about unethical business practices within 23 concrete CSR-related topics from various sources such as NGOs, global media, or company reports. These topics include, for example, child labor, excessive environmental pollution, data privacy issues, bribery, and tax fraud. Refintiv assigns the company a value between 0 and 100, based on the total amount of scandals a company is involved in a fiscal year relative to its peer industry group. Larger scandals often affect multiple topics, and if the company is, for example, involved in an ongoing lawsuit, the scandal is accounted for over multiple years. Thus, the score allows for differentiation of the severity and magnitude of scandals. Generally, if a company is involved in a scandal, the score decreases. However, to allow an intuitive interpretation so that high values indicate more corporate scandals, we rescale the score as follows: 100 minus *Controversies Score*. Throughout the rest of the paper, we refer to the rescaled version of the score. To ensure robust results, we employ an alternative measure of CSI in section 7.4.3.

[10] Note that a scandal is not always an illegal action (Godfrey, 2005) and that we require both the unethical behavior as well as its disclosure, as stakeholders can only act on publicly known information.

Refinitiv's *ESG Score* and *Controversies Score* find numerous applications in scientific publications (see e.g., Ioannou and Serafeim, 2012; Liang and Renneboog, 2017; Aouadi and Marsat, 2018; Cao et al., 2019; Dyck et al., 2019; Flammer, 2021; Dai et al., 2021; Dorfleitner et al., 2022) and are considered to be one of the most extensive and transparent CSR- and CSI-related datasets (see Cheng et al., 2014a; Durand and Jacqueminet, 2015).

### 7.3.3 Further independent firm-level variables

In light of the rich literature on corporate payout, we need to control for various firm-level determinants linked to a firm's payout decision.

According to the life-cycle theory (see e.g., DeAngelo et al., 2006; Denis and Osobov, 2008; Fama and French, 2001; Mueller, 1972), a firm's payout policy changes over different life-cycle stages. Compared with mature companies, early-stage firms are more likely to face financial constraints and generally have more growth opportunities. This reduces the amount of available free cash flows and thus restricts the ability of young firms to pay dividends or repurchase stocks. As firms mature, they achieve more stable cash flows and can more easily access external financing at lower costs to finance their investments. It follows that the agency costs of cash retention increase (Denis and Osobov, 2008; DeAngelo et al., 2006), and consequently, these firms have more incentives as well as more spare resources for payout (Fenn and Liang, 2001; Benlemlih, 2019; De Cesari and Ozkan, 2015). In line with the literature, we account for this and add a *Size* variable (the logarithm of one plus total assets). As an additional proxy for a firm's life cycle, we include the variable *Retained Earnings (RE)*, defined as the ratio of payout-adjusted retained earnings to the book value of equity.[11] High *Retained Earnings* are associated with companies in the later stages of the life cycle because these firms are more likely able to self-finance most of their investments and thus are expected to have a higher payout (DeAngelo et al., 2006; De Cesari and Ozkan, 2015; Denis and Osobov, 2008).

Firms may value the signaling mechanisms through dividend payment or stock repurchase more if external stakeholders have little information about the company (DeAngelo et al., 2006). We cover aspects of firm visibility within the variable *Analyst Coverage (AC)*, which is the logarithm of 1 plus the number of analysts providing earnings forecasts for the firm.[12] These analysts help to reduce information asymmetries about the firm's financial performance (El Ghoul et al., 2011), allow investors more precise estimations about future growth opportunities (Agarwal and Chakraverty, 2023), and consequently reduce the

[11] We find similar results if we define *RE* as the ratio of payout-adjusted retained earnings to total assets. Note that the coefficients of *RE* in the OLS regression on *Rep* become positive and statistically significant, further supporting the life-cycle theory.

[12] In line with Blankespoor et al. (2014) and Bhattacharya and Jacobsen (2016), we set missing values for *Analyst Coverage* to 0.

reliance on signaling mechanisms.

Next, we include the variables *Leverage* (Lev), which is the ratio of total long-term debt to total assets and *Cash*, defined as the ratio of cash and short-term investments to total assets. Following the agency problem of free cash flow, high levels of *Cash* are indicative of managerial opportunism and firms can use dividend payouts and stock repurchases to limit these agency conflicts (De Cesari and Ozkan, 2015; Benlemlih, 2019). In comparison, debt holders scrutinize and monitor highly levered firms and thus already restrict managerial opportunism, which reduces the need to use payout policy in controlling agency problems (Easterbrook, 1984; Renneboog and Trojanowski, 2011; Von Eije and Megginson, 2008; De Cesari and Ozkan, 2015). In addition, we account for the phenomenon of "financed payouts" (Farre-Mensa et al., 2021), i.e. that a substantial amount of firms finance their payout with an increase in debt.[13] However, firms with high leverage may also face certain financial constraints, such as restrictive debt covenants, which may limit the company's freedom to pay dividends or restrains the repurchase of shares (Renneboog and Trojanowski, 2011; Von Eije and Megginson, 2008; Fenn and Liang, 2001).

We account for growth opportunities within the variable *Market-to-Book (MTB)*, which is the logarithm of 1 plus the market value of a firm's equity divided by the book value of equity. Firms with fewer available investment opportunities are more likely to use free cash flows for dividends or stock repurchases (De Cesari and Ozkan, 2015; Kahle, 2002; Baker and Wurgler, 2004; Agarwal and Chakraverty, 2023).

Finally, as firms with high profitability earn higher free cash flows and can distribute them more freely (De Cesari and Ozkan, 2015; Benlemlih, 2019), one might argue that CSR and CSI affect corporate payout decisions through their (positive or negative) impact on a firm's profitability. Consequently, we need to decouple CSR and CSI from a firm's profitability, which enables a more unbiased examination of our underlying theories discussed earlier. For that, we control for the company's profitability within the variable *Return on Assets (ROA)*, defined as the ratio of operating income before depreciation to total assets.

### 7.3.4 Summary Statistics

All currency-dependent variables are converted to US Dollars with the mean of monthly spot exchange rates within the corresponding year.[14] We winsorize all variables (except for our measures for CSR and CSI) on the 1 percent and 99 percent level. Furthermore, in accordance with the literature (see e.g. Whited and Wu, 2006; Farre-Mensa and Ljungqvist, 2016; Heider and Ljungqvist, 2015; Denis and Osobov, 2008; Fama and French, 2001), we

[13] Farre-Mensa et al. (2021) estimate that for US firms from 1989 to 2019, 41% of aggregate net debt proceeds are used to finance dividends and share repurchases within the same year the new debt was raised.

[14] Data on historical exchange rates are obtained from Thomson Reuters Datastream.

exclude all utility firms (SIC code between 4900 and 4999) and financial firms (SIC code between 6000 and 6999) since there may be external regulatory rules that restrict their payout policies (De Cesari and Ozkan, 2015). We also remove all firm-year observations with missing values or with negative *Size*.

Our final sample consists of 47,867 firm-year observations with 7,260 distinct publicly listed firms across 77 countries from 2003 to 2021. The sample size increases over time because Refinitiv expands its rating universe. Table 7.1 displays the number of firms per year in our sample. The sample distribution across 2-digit SIC industry sectors and continents is presented in table 7.2. Table A.3 in the appendix presents the number of firms per country.

Table 7.1: Number of firm observations per year.

| $Year$ | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 |
|---|---|---|---|---|---|---|---|---|---|---|
| $N$ | 564 | 566 | 1,054 | 1,298 | 1,309 | 1,453 | 1,676 | 1,994 | 2,409 | 2,507 |
| $Year$ | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | |
| $N$ | 2,592 | 2,661 | 2,674 | 3,166 | 3,681 | 4,371 | 4,829 | 5,410 | 3,653 | |

This table reports the number of firms per year in our data set.

Table 7.3.4 reports the descriptive statistics for our sample. Median and mean of the *Controversies Score* show that most of our firms are not involved in a scandal. When comparing the median and mean of our two payout dummy variables ($D_{Rep}$ and $D_{Div}$), the sample would indicate that, overall, firms prefer paying dividends over repurchasing shares. However, in closer examination over time, we can confirm the well-documented shift toward stock repurchases (see e.g., Jagannathan et al., 2000; Fama and French, 2001; Skinner, 2008). Figure 1 displays this trend and presents the percentage of US firms within our sample that pay dividends (i.e., $D_{Div}$ equals one) on the left and the percentage of firms that repurchase their shares ($D_{Rep}$ equal to one) on the right. Moreover, in line with the literature, we document a sharp decline in payout during the 2008/09 financial crisis (Bliss et al., 2015) and during the Covid-19 pandemic (Ntantamis and Zhou, 2022).

In figure 7.2, we expand this analysis and present the propensity of US companies to pay dividends or to repurchase stocks depending on the firm's *ESG Score* or *Controversies Score* each year. Apparently, firms with above-median *ESG Scores*, displayed with solid lines, are more likely to pay dividends and to repurchase stocks than firms with below-median scores (dashed lines). Contrarily, companies with below-median *Controversies Scores* are more likely to repurchase stocks, while no clear trend regarding the propensity to pay dividends can be identified.

Table 7.4 presents the correlation matrix. The positive correlation between *Rep* and *Div* ($0.19^{***}$) supports the reasoning that these two payout channels are used in a complementary way rather than as substitutes (see e.g., De Cesari and Ozkan, 2015; Jagannathan et al.,

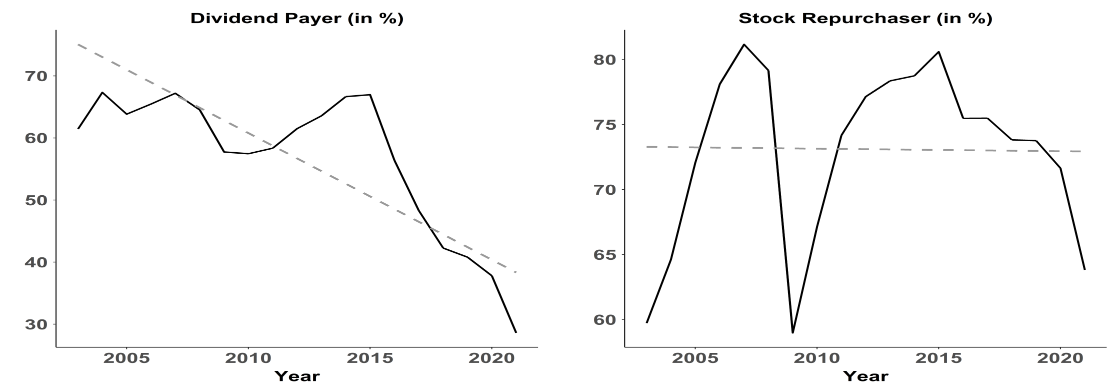
Table 7.2: Sample characteristics

| **Panel A.** Sample distribution by industry sectors. | | |
|---|---|---|
| Standard Industry Classification (SIC) | N | Freq. |
| Manufacturing | 3,724 | 51.29% |
| Services | 1,342 | 18.48% |
| Transport and Communication | 607 | 8.36% |
| Mining | 542 | 7.47% |
| Retail Trade | 491 | 6.76% |
| Wholesales Trade | 226 | 3.11% |
| Construction | 205 | 2.82% |
| Others | 85 | 1.17% |
| Agriculture, forestry and fishing | 38 | 0.52% |
| **Total** | 7,260 | 100% |

| **Panel B.** Sample distribution by continents. | | |
|---|---|---|
| Continent | N | Freq. |
| North America | 2,855 | 39.33% |
| Asia | 1987 | 27.37% |
| Europe | 1708 | 23.53% |
| Oceania | 438 | 6.03% |
| South America | 156 | 2.15% |
| Africa | 116 | 1.6% |
| **Total** | 7,260 | 100% |

This table shows additional sample characteristics. Our sample includes 7,260 distinct firms from 2003 to 2021. Panel A reports the number of firms (N) and their fraction of the total sample (Freq.) per industry based on the 2-digit SIC code, and Panel B for each continent. We excluded financial firms (SIC codes between 6000 and 6999) and utility firms (SIC codes between 4900 and 4999). The continent classification refers to the country in which the firm is headquartered.

Figure 7.1: Dividends and stock repurchases in the US.




This figure shows the percentage of US firms within our sample that pay dividends (left) and that repurchase stocks (right) over time. The dashed lines represent the trend lines.

Table 7.3: Descriptive statistics

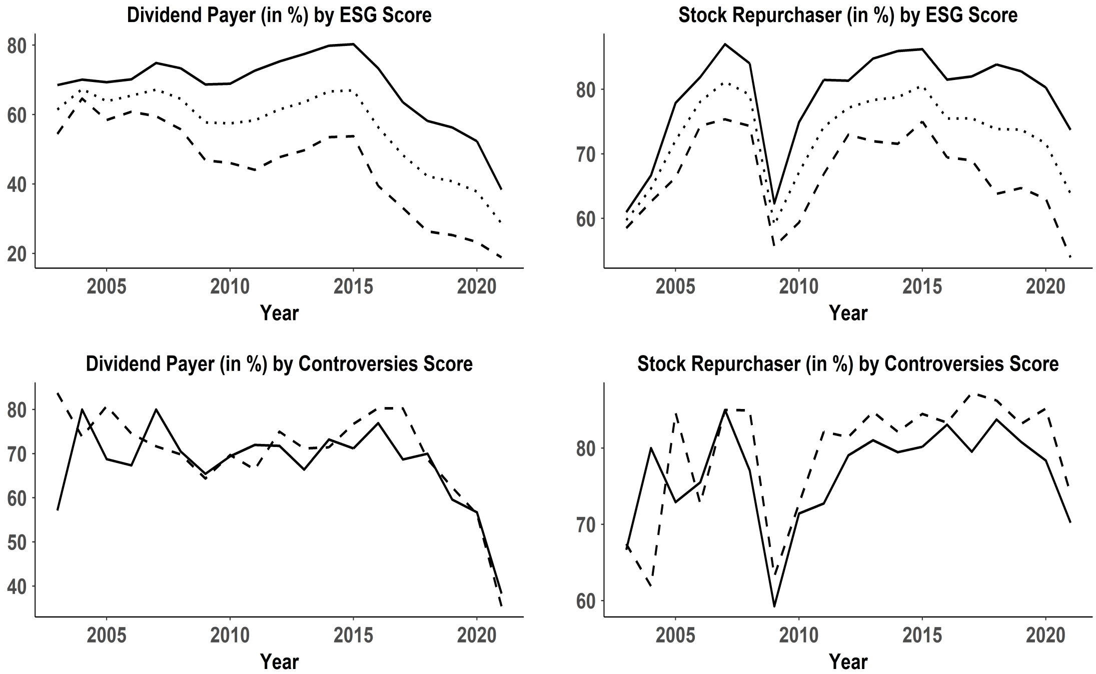
| Variable | N | Min | Median | Max | Mean | St. Dev. |
|---|---|---|---|---|---|---|
| Dependent variables | | | | | | |
| *Rep* | 47,867 | 0.00 | 0.00 | 7.60 | 1.26 | 2.24 |
| $D_{Rep}$ | 47,867 | 0 | 0 | 1 | 0.31 | 0.46 |
| *Div* | 47,867 | 0.00 | 3.29 | 7.62 | 2.77 | 2.46 |
| $D_{Div}$ | 47,867 | 0 | 1 | 1 | 0.61 | 0.49 |
| Measurement of CSR and CSI | | | | | | |
| *CS* | 47,867 | 0 | 0 | 99 | 8.13 | 21.48 |
| *ESG* | 47,867 | 0.35 | 38.45 | 95.15 | 40.78 | 20.48 |
| Firm-level control variables | | | | | | |
| *Size* | 47,867 | 2.65 | 8.10 | 11.97 | 8.04 | 1.63 |
| *RE* | 47,867 | −17.57 | 0.00 | 3.48 | −0.02 | 1.53 |
| *AC* | 47,867 | 0.00 | 2.30 | 3.40 | 2.13 | 0.88 |
| *Cash* | 47,867 | 0.00 | 0.11 | 0.97 | 0.16 | 0.18 |
| *Lev* | 47,867 | 0.00 | 0.15 | 0.72 | 0.18 | 0.15 |
| *MTB* | 47,867 | 0.01 | 1.14 | 4.84 | 1.30 | 0.78 |
| *ROA* | 47,867 | −1.06 | 0.11 | 0.49 | 0.11 | 0.13 |
| Alternative measures for CSR and CSI | | | | | | |
| *NoS* | 47,867 | 0 | 0 | 4.70 | 0.17 | 0.46 |
| *Env* | 47,867 | 0.00 | 27.1 | 99 | 32.03 | 28.47 |
| *Soc* | 47,867 | 0.05 | 37.81 | 98.63 | 40.88 | 23.60 |
| *Gov* | 47,867 | 0.16 | 47.72 | 99.33 | 47.78 | 22.49 |

This table reports the descriptive statistics (number of observations, minimum, median, maximum, mean, and standard deviation) of the final sample. The sample includes 7,260 distinct firms from 2003 to 2021. We winsorize all variables (except the measures for CSR and CSI) at the 1 and 99 percent level for each year. The alternative measures for CSR and CSI are discussed in section 7.4.3. A detailed description of our variables can be found in table A in the appendix.

2000; Grullon and Michaely, 2002), and justifies our use of both channels separately. Moreover, the positive correlation between *Size* and *Div* ($0.52^{***}$) as well as between *Size* and *ESG Score* ($0.48^{***}$) is in line with the life-cycle theory (see e.g., Fama and French, 2001; DeAngelo et al., 2006) or the size effect on CSR (see e.g., Drempetic et al., 2019).

Supported by the positive correlation between *ESG* and *CS* ($0.25^{***}$) in table 7.4, our sample indicates that CSR and CSI are not two mutually exclusive dimensions but rather two different concepts. Table 7.5 provides additional anecdotal evidence on this relation for well-known scandals. It depicts the *Controversies Score* and the *ESG Score*, illustrating that all of these companies achieved a high ESG rating in the same year that they were involved in a major scandal. In addition, the table shows the environmental (*Env*), social (*Soc*), and corporate governance (*Gov*) pillars for these companies, with the pillar corresponding

Figure 7.2: Corporate payout depending on CSR and CSI.




This figure shows the percentage of US firms within our sample that pay dividends (left) and that repurchase stocks (right) depending on the *ESG Score* and *Controversies Score*. For the *ESG Score*, we split the full sample (dotted line) into firms with above-median scores (solid line) and below-median scores (dashed line) each year. Regarding the *Controversies Score*, we split the sample of firms with a non-zero score into above-median (solid line) and below-median (dashed line).

to the topic of the scandal in bold.

Table 7.4: Correlation Matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) $Rep$ | 1 | | | | | | | | | | | | |
| (2) $D_{Rep}$ | 0.85 | 1 | | | | | | | | | | | |
| (3) $Div$ | 0.19 | 0.06 | 1 | | | | | | | | | | |
| (4) $D_{Div}$ | 0.08 | 0 | 0.9 | 1 | | | | | | | | | |
| (5) $CS$ | 0.19 | 0.12 | 0.15 | 0.05 | 1 | | | | | | | | |
| (6) $ESG$ | 0.14 | 0.04 | 0.35 | 0.2 | 0.25 | 1 | | | | | | | |
| (7) $Size$ | 0.28 | 0.12 | 0.52 | 0.33 | 0.31 | 0.48 | 1 | | | | | | |
| (8) $RE$ | 0.21 | 0.14 | 0.24 | 0.24 | 0.07 | 0.14 | 0.3 | 1 | | | | | |
| (9) $AC$ | 0.18 | 0.06 | 0.22 | 0.15 | 0.11 | 0.23 | 0.37 | 0.11 | 1 | | | | |
| (10) $Cash$ | -0.05 | -0.02 | -0.23 | -0.24 | -0.06 | -0.19 | -0.39 | -0.32 | -0.06 | 1 | | | |
| (11) $Lev$ | 0.13 | 0.16 | 0.01 | -0.03 | 0.07 | 0.1 | 0.24 | -0.03 | 0.04 | -0.31 | 1 | | |
| (12) $MTB$ | 0.12 | 0.09 | -0.04 | -0.09 | -0.01 | -0.02 | -0.2 | -0.14 | 0.09 | 0.23 | 0.08 | 1 | |
| (13) $ROA$ | 0.19 | 0.12 | 0.3 | 0.29 | 0.05 | 0.15 | 0.26 | 0.51 | 0.22 | -0.4 | 0.04 | 0.07 | 1 |

This table reports the correlation matrix for the employed variables. A detailed description of our variables can be found in table A.1 in the appendix.

Table 7.5: Anecdotal evidence on the relation between CSR and CSI

| | Siemens (2008) | BP (2010) | VW (2015) | Wells Fargo (2016) | Apple (2017) | Kobe Steel (2018) | Meta (2018) |
|---|---|---|---|---|---|---|---|
| *CS* | 95 | 99.91 | 98.08 | 98 | 86, 36 | 99.07 | 99.11 |
| *ESG* | 88.93 | 87.58 | 80.18 | 81.19 | 67.94 | 59.11 | 43.06 |
| *Env* | 85.72 | **77.25** | **86.07** | 91.48 | 55.47 | 61.07 | 40.61 |
| *Soc* | 86.67 | 93.12 | **82.11** | 77.20 | **63.97** | **41.75** | **59.29** |
| *Gov* | **97.33** | 92.87 | 68.64 | **84.67** | 85.41 | 84.77 | 29.81 |

This table provides anecdotal evidence on the relation between CSR and CSI for well-known corporate scandals, such as Siemens bribing the Argentine government in 2008, BP's Deepwater Horizon oil spill in 2010, VW's emission scandal in 2015, Wells Fargo creating fake deposit and credit card accounts in 2016, Apple's 'batterygate' in 2017, Kobe Steel's product safety concerns in 2018, and Meta's (former Facebook) Cambridge Analytica data leak in 2018. Additionally, the environmental (*Env*), social (*Soc*), and corporate governance (*Gov*) pillars of the *ESG Score* are displayed. The pillars corresponding to the scandal's topic are highlighted in bold.

## 7.4 Results

### 7.4.1 Baseline results

We employ an OLS regression and 2SLS regression with fixed effects and firm-level clustered standard errors to derive insights on the linkage of a firm's *ESG Score*, $ESG^{est}$, and *Controversies Score* with the amount of dividend payment (*Div*) and stock repurchases (*Rep*). Based on La Porta et al. (2000), we need to account for national differences that might affect a firm's payout policies, such as disparities in shareholder rights protection, dividend taxation, and share repurchase laws. By using time-fixed effects, we capture the trend toward stock repurchases (see e.g., Jagannathan et al., 2000; Fama and French, 2001) and account for the impact of general economic conditions on the firm's payout (such as the effect of the 2008/09 financial crisis documented by Bliss et al., 2015). Finally, within the firm-fixed effects, we cover further unobserved heterogeneity, such as the preference for stock repurchases over paying dividends, when executive compensation is highly based on stock options (see e.g., Fenn and Liang, 2001; Kahle, 2002; Dittmar and Dittmar, 2008; Dittmar and Field, 2015), or a firm's preference to smooth dividends (Lintner, 1956; Von Eije and Megginson, 2008). We lag all independent variables by one year to further reduce a possible endogeneity bias.

Table 7.6 presents our baseline results. Columns (1) to (4) report the regression coefficients for *Rep* as the dependent variable, and columns (5) to (8), if we employ *Div*. The coefficient of the *Controversies Score* is statistically significant and negative across all settings. Companies involved in scandals spend less financial resources on dividends and stock repurchases. Our results do not show conclusive evidence for market timing but instead support the theory of precautionary cash holding. Managers miss the opportunity of pricing uncertainty to buy back shares after a scandal because they may fear tightening financial constraints following the scandal. This could lead managers to hoard cash to secure future investments rather than to distribute spare financial resources via dividends or repurchases.

Regarding the *ESG Score* and $ESG^{est}$ *Score*, we find positive and statistically significant coefficients for the relation with *Div.* Firms with high scores tend to pay more dividends because they can use these dividends to restrict the agency problem of free cash flow arising from managers' incentives to overinvest in CSR. Interestingly, the coefficient becomes negative when we consider the relation between the *ESG* and $ESG^{est}$ with *Rep.* However, the coefficients are insignificant, so we cannot support the signaling mechanism of payout in the context of CSR. Overall, these results support the view that corporate payout policy serves to control agency problems, (Easterbrook, 1984), and that payout decisions can be better understood with agency theory than by signaling (Lambrecht and Myers, 2012; Hasan and Uddin, 2022; Allen and Michaely, 2003; DeAngelo et al., 2009; Leary and Michaely, 2011).

Moreover, most of our controls are in line with the expected relation documented in the literature. First, we observe a statistically significant and positive coefficient on the *Size* variable. In accordance with the life-cycle theory (see e.g., DeAngelo et al., 2006; Fama and French, 2001; Denis and Osobov, 2008), larger firms pay more dividends and spend more financial resources on stock repurchases. Consistent with the implications of agency problems on the payout decision, we document a statistically significant negative effect of *Leverage* and a positive and statistically significant effect of *Cash* in all settings (see e.g., Easterbrook, 1984; Renneboog and Trojanowski, 2011; Von Eije and Megginson, 2008; Benlemlih, 2019; Fenn and Liang, 2001). Furthermore, we can also confirm the positive link between *ROA* and corporate payout across all settings, as documented by De Cesari and Ozkan (2015) and Benlemlih (2019). Finally, the *Analyst Coverage* variable exhibits a statistically significant and positive coefficient. Consistent with Bhattacharya and Jacobsen (2016), our findings again do not support evidence in favor of signaling mechanisms of payout policies since a high *Analyst Coverage* proxies a low level of asymmetric information.

### 7.4.2 Implications of CSR and CSI on the propensity to pay dividends or to repurchase stocks

Considering the implications of figure 2, we expand our methodology and employ a fixed-effects logistic regression proposed by Stammann et al. (2016) to examine how a firm's *ESG Score* and *Controversies Score* might be linked with the propensity to pay dividends ($D_{Div}$)

Table 7.6: OLS and 2SLS regressions with fixed-effects

| | *Stock Repurchase* (*Rep*) | | | | *Dividends* (*Div*) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $CS_{t-1}$ | −0.0020*** | | −0.0020*** | −0.0019* | −0.0012* | | −0.0013* | −0.0037** |
| | (−3.6464) | | (−3.5897) | (−2.2445) | (−2.3549) | | (−2.4843) | (−2.9008) |
| $ESG_{t-1}$ | | −0.0021 | −0.0020 | | | 0.0036** | 0.0037** | |
| | | (−1.8188) | (−1.6919) | | | (2.8135) | (2.8926) | |
| $ESG^{est}_{t-1}$ | | | | −0.0084 | | | | 0.1387* |
| | | | | (−0.1667) | | | | (2.1266) |
| $Size_{t-1}$ | 0.3543*** | 0.3582*** | 0.3607*** | 0.3819* | 0.5121*** | 0.4986*** | 0.5002*** | 0.0666 |
| | (8.8615) | (8.8253) | (8.8947) | (2.3428) | (11.3281) | (11.0426) | (11.0937) | (0.3150) |
| $RE_{t-1}$ | −0.0041 | −0.0039 | −0.0039 | −0.0035 | 0.0056 | 0.0053 | 0.0053 | −0.0062 |
| | (−0.4024) | (−0.3803) | (−0.3859) | (−0.3863) | (0.4574) | (0.4375) | (0.4342) | (−0.4887) |
| $AC_{t-1}$ | 0.0493 | 0.0532 | 0.0520 | 0.0609 | 0.1774*** | 0.1731*** | 0.1724*** | −0.0127 |
| | (1.6486) | (1.7742) | (1.7357) | (0.8381) | (5.3774) | (5.2538) | (5.2309) | (−0.1365) |
| $Cash_{t-1}$ | 0.4838*** | 0.4850*** | 0.4847*** | 0.4882*** | 0.5579*** | 0.5563*** | 0.5561*** | 0.4986*** |
| | (3.5048) | (3.5153) | (3.5120) | (5.0254) | (3.3766) | (3.3681) | (3.3682) | (3.6504) |
| $Lev_{t-1}$ | −1.1345*** | −1.1396*** | −1.1324*** | −1.1302*** | −0.9998*** | −1.0085*** | −1.0038*** | −1.1470*** |
| | (−7.7959) | (−7.8345) | (−7.7845) | (−10.5869) | (−6.3916) | (−6.4480) | (−6.4294) | (−8.0510) |
| $MTB_{t-1}$ | 0.0730** | 0.0755** | 0.0740** | 0.0780** | 0.2220*** | 0.2212*** | 0.2202*** | 0.1520*** |
| | (2.7856) | (2.8757) | (2.8241) | (2.5901) | (7.5905) | (7.5631) | (7.5406) | (3.6528) |
| $ROA_{t-1}$ | 1.6561*** | 1.6735*** | 1.6575*** | 1.6618*** | 2.1624*** | 2.1704*** | 2.1599*** | 2.0703*** |
| | (9.4467) | (9.5222) | (9.4582) | (14.7801) | (11.1599) | (11.2079) | (11.1592) | (13.4593) |
| *Constant* | −4.0400*** | −4.0468*** | −4.0787*** | −4.2047*** | −6.0023*** | −5.9098*** | −5.9306*** | −3.3153** |
| | (−13.3889) | (−13.2942) | (−13.3921) | (−4.2652) | (−16.9062) | (−16.7251) | (−16.8075) | (−2.5771) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,867 | 47,867 | 47,867 | 47,867 | 47,867 | 47,867 | 47,867 | 47,867 |
| Adjusted $R^2$ | 0.6885 | 0.6883 | 0.6886 | 0.6880 | 0.7559 | 0.7560 | 0.7561 | 0.5388 |
| VIF (max) | 1.6581 | 1.8182 | 1.9123 | | 1.6581 | 1.8182 | 1.9123 | |

This table reports the results of the OLS and 2SLS regression with firm- and year-fixed effects. Standard errors are clustered on the firm level. Columns (1) to (4) present the results for stock repurchases (*Rep*), and columns (5) to (8) for dividends (*Div*). Results of the second stage of the 2SLS are displayed in columns (4) and (8). Following El Ghoul et al. (2011), we use the two-digit SIC industry average ESG score (excluding the respective firm) as an exogenous instrument to estimate $ESG^{est}_{t-1}$ in the first stage of the 2SLS regression. A detailed description of our variables can be found in table A in the appendix. The adjusted $R^2$ and the maximum variance inflation factor (VIF) are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

or to repurchase shares ($D_{Rep}$).[15] In accordance with the literature (see e.g., Von Eije and Megginson, 2008), we employ the same set of controls as in the previous section. Columns (1) to (3) of table 7.7 report the results for $D_{Rep}$, and columns (4) to (6) for $D_{Div}$.

The majority of our previous results remain unchanged. The positive and statistically significant coefficient of the *ESG Score* on $D_{Div}$ in columns (5) and (6) show that firms with high *ESG Scores* are more likely to pay dividends, which is in line with the arguments regarding the agency problems of CSR. The most notable difference comes with the *Controversies Score*. The coefficients for the propensity to repurchase are still negative and statistically significant, while the effect on the likelihood of paying dividends is insignificant. Managers are reluctant to forgo dividends altogether, even when they fear tightening financial frictions following a scandal. Instead, managers prefer to cut stock repurchases

[15] Note that we rely on annual data, and thus $T$ is relatively small within our sample. To account for the incidental parameter bias problem for samples with small $T$, we apply the analytical bias correction derived by Fernández-Val (2009).

prior to any change in dividend policy.

Table 7.7: Logistic regression with fixed effects

| | *Repurchase Dummy* ($D_{Rep}$) | | | *Dividend Dummy* ($D_{Div}$) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $CS_{t-1}$ | $-0.0036^{***}$ | | $-0.0035^{***}$ | $-0.0012$ | | $-0.0014$ |
| | (0.0011) | | (0.0011) | (0.0011) | | (0.0011) |
| $ESG_{t-1}$ | | $-0.0051$ | $-0.0047$ | | $0.0104^{***}$ | $0.0105^{***}$ |
| | | (0.0027) | (0.0027) | | (0.0024) | (0.0024) |
| $Size_{t-1}$ | $0.5733^{***}$ | $0.5782^{***}$ | $0.5858^{***}$ | $0.8297^{***}$ | $0.7887^{***}$ | $0.7903^{***}$ |
| | (0.0652) | (0.0655) | (0.0656) | (0.0629) | (0.0636) | (0.0636) |
| $RE_{t-1}$ | $-0.0592^{*}$ | $-0.0584^{*}$ | $-0.0585^{*}$ | $0.4488^{***}$ | $0.4444^{***}$ | $0.4435^{***}$ |
| | (0.0280) | (0.0280) | (0.0280) | (0.0692) | (0.0690) | (0.0689) |
| $AC_{t-1}$ | 0.0182 | 0.0260 | 0.0255 | $0.3575^{***}$ | $0.3410^{***}$ | $0.3399^{***}$ |
| | (0.0636) | (0.0637) | (0.0637) | (0.0547) | (0.0548) | (0.0548) |
| $Cash_{t-1}$ | $0.9530^{**}$ | $0.9671^{**}$ | $0.9595^{**}$ | $0.7679^{*}$ | $0.7391^{*}$ | $0.7379^{*}$ |
| | (0.3601) | (0.3600) | (0.3602) | (0.3300) | (0.3303) | (0.3303) |
| $Lev_{t-1}$ | $-1.9543^{***}$ | $-1.9520^{***}$ | $-1.9401^{***}$ | $-1.2240^{***}$ | $-1.2525^{***}$ | $-1.2428^{***}$ |
| | (0.2948) | (0.2948) | (0.2951) | (0.2665) | (0.2667) | (0.2669) |
| $MTB_{t-1}$ | 0.0668 | 0.0725 | 0.0697 | $0.1736^{**}$ | $0.1746^{**}$ | $0.1730^{**}$ |
| | (0.0664) | (0.0665) | (0.0665) | (0.0565) | (0.0566) | (0.0566) |
| $ROA_{t-1}$ | $5.0853^{***}$ | $5.1660^{***}$ | $5.1098^{***}$ | $8.1575^{***}$ | $8.1079^{***}$ | $8.0912^{***}$ |
| | (0.4561) | (0.4565) | (0.4567) | (0.4617) | (0.4617) | (0.4618) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 13,587 | 13,587 | 13,587 | 17,270 | 17,270 | 17,270 |
| Mcfadden-Pseudo $R^2$ | 0.6355 | 0.6353 | 0.6356 | 0.7072 | 0.7076 | 0.7076 |
| Log-Lik. | $-6474.2279$ | $-6478.6869$ | $-6472.4178$ | $-7933.5061$ | $-7922.9776$ | $-7922.0284$ |

This table reports the logistic regression results with year- and firm-fixed effects. Standard errors are clustered on the firm level. Columns (1) to (3) present the results for the propensity to repurchase stocks ($D_{Rep}$), and columns (4) to (6) the propensity to pay dividends ($D_{Div}$). A detailed description of our variables can be found in table A in the appendix. Note that the fixed-effects logistic regression requires variation in the binary dependent variable ($D_{Rep}$ or $D_{Div}$), i.e. the firm has to change from a payer (repurchaser) to a non-payer (non-repurchaser) or vice versa at a given point in time, which reduces our sample size. Mcfadden-Pseudo $R^2$ and the log-likelihood are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

### 7.4.3 Robustness and economic significance

In this section, we implement several tests to ensure the robustness of our previous results. First, table 7.2 shows that roughly 40% of our firms are located in North America, and over 50% are in the manufacturing sector. We address this issue by excluding the US and manufacturing sector and repeating our previous analysis. Table A.4 in the appendix presents the results for the fixed-effects logistic regression for a US-only sample and a sample excluding the US. In table A.5, we exclude the manufacturing sector. Overall, our results are robust to these exclusion criteria, and we can confirm the previous findings.

Moreover, recent literature has expressed numerous concerns regarding the measurement of CSR. Dorfleitner et al. (2015) and Chatterji et al. (2016) discuss the lack of comparability between different ESG ratings. Berg et al. (2022) argue that a rating agency's general view of a company may distort ESG ratings, while Berg et al. (2020) criticize the potential black-box nature and rewriting of ESG ratings. In addition, Benlemlih (2019) and Samet and Jarboui (2017) highlight that using an aggregated ESG score might conceal the true effect of CSR on a company's payout policy.

We attempt to address some of these concerns and limit the potential bias of relying on a single score. First, instead of using the aggregated *Controversies Score* as our measure for CSI, we employ the actual count of scandals a company is involved in a given year. To account for the presumable non-linear effect of a count variable, we define the *Number of Scandals (NoS)* variable as the logarithm of one plus the count of scandals for the 23 CSR-related topics. This approach allows us to alleviate concerns about the methodology behind the score (such as weighting or industry effects) or the rating agency bias while still considering the scandal's severity and magnitude. Finally, relying on the actual count of scandals facilitates economic interpretation.

Next, we dissect the overall *ESG Score* into its three pillars (environment, social and corporate governance). This approach provides further insight into different aspects of CSR, as poor performance in a particular pillar can be offset by good performance in the other two. The *Environmental Score (Env)* measures a company's efforts to reduce resource use or environmental pollution, while the *Social Score (Soc)* accounts for product and employee safety, diversity, and data privacy. Finally, the *Governance Score (Gov)* captures aspects of shareholder rights protection, the implementation and management of CSR strategies, and the transparency of CSR reporting. Table 7.3.4 displays descriptive statistics for these measures.[16]

Columns (1) and (2) of table 7.8 present the coefficients for the OLS regression on the payout levels (*Rep* and *Div*) and columns (3) and (4) for the logistic regression on the propensity to repurchase stocks ($D_{Rep}$) or to pay dividends ($D_{Div}$).

Most of our previous results can be confirmed. The coefficient of *NoS* is statistically significant and negative for the likelihood of and the financial resources spent on stock repurchases. In terms of economic significance, a one standard deviation increase in *NoS*, ceteris paribus, decreases the amount of financial resources distributed via stock repurchases by 3.76 percent. At the same time, the relationship of *NoS* with *Div* and $D_{Div}$ is negative but insignificant, which supports the view that managers try to avoid reductions in dividends (DeAngelo et al., 2009; Larkin et al., 2017) and prefer to cut investments (Brav et al., 2005; Bliss et al., 2015) or stock repurchases before lowering dividend payout.

Regarding a firm's environmental performance, our results show a positive and statistically significant coefficient of *Env* in almost all settings. Especially with the recent trend toward

[16] Note that the majority of firms in our sample are not involved in a scandal. However, there are also high profile events with a large *NoS*, such as the Meta (former Facebook) Cambridge Analytica data leak scandal in 2018 with a total of 109 reports in one year.

Table 7.8: Number of scandals and ESG pillars

| | OLS regression with fixed-effects | | Logistic regression with fixed-effects | |
|---|---|---|---|---|
| | *Rep* | *Div* | $D_{Rep}$ | $D_{Div}$ |
| | (1) | (2) | (3) | (4) |
| $NoS_{t-1}$ | −0.0819* | −0.0307 | −0.1660** | −0.0388 |
| | (−2.2951) | (−0.9748) | (0.0554) | (0.0612) |
| $Env_{t-1}$ | 0.0018 | 0.0035** | 0.0044* | 0.0092*** |
| | (1.7575) | (3.2658) | (0.0021) | (0.0019) |
| $Soc_{t-1}$ | −0.0036*** | −0.0004 | −0.0086*** | −0.0016 |
| | (−3.5735) | (−0.3834) | (0.0024) | (0.0021) |
| $Gov_{t-1}$ | −0.0002 | 0.0010 | −0.0015 | 0.0036* |
| | (−0.2539) | (1.3409) | (0.0017) | (0.0015) |
| $Size_{t-1}$ | 0.3602*** | 0.4958*** | 0.5911*** | 0.7756*** |
| | (8.9142) | (11.0187) | (0.0658) | (0.0638) |
| $RE_{t-1}$ | −0.0042 | 0.0050 | −0.0580* | 0.4412*** |
| | (−0.4055) | (0.4099) | (0.0281) | (0.0689) |
| $AC_{t-1}$ | 0.0510 | 0.1721*** | 0.0210 | 0.3402*** |
| | (1.7065) | (5.2136) | (0.0639) | (0.0548) |
| $Cash_{t-1}$ | 0.4847*** | 0.5596*** | 0.9442** | 0.7424* |
| | (3.5101) | (3.3908) | (0.3604) | (0.3306) |
| $Lev_{t-1}$ | −1.1485*** | −1.0146*** | −1.9600*** | −1.2703*** |
| | (−7.8842) | (−6.4939) | (0.2954) | (0.2672) |
| $MTB_{t-1}$ | 0.0759** | 0.2210*** | 0.0764 | 0.1775** |
| | (2.8992) | (7.5769) | (0.0665) | (0.0566) |
| $ROA_{t-1}$ | 1.6682*** | 2.1692*** | 5.1424*** | 8.1456*** |
| | (9.4785) | (11.2022) | (0.4565) | (0.4623) |
| *Constant* | −4.0721*** | −5.8773*** | | |
| | (−13.3233) | (−16.6915) | | |
| Fixed effects | Yes | Yes | Yes | Yes |
| Observations | 47,867 | 47,867 | 13,587 | 17,270 |
| Adjusted/Mcfadden $R^2$ | 0.6886 | 0.7561 | 0.6359 | 0.5545 |
| VIF (max)/Log-Lik. | 2.5097 | 2.5097 | −6466.6967 | −7913.3995 |

This table reports the results of the OLS regression with firm-, year-, and country-fixed effects (columns 1 and 2) and of the logistic regression with year- and firm-fixed effects (columns 3 and 4). Standard errors are clustered on the firm level. A detailed description of our variables can be found in table A in the appendix. Note that the fixed-effects logistic regression requires variation in the binary dependent variable ($D_{Rep}$ or $D_{Div}$), i.e. the firm has to change from a payer (repurchaser) to a non-payer (non-repurchaser) or vice versa at a given point in time, which reduces our sample size. Adjusted $R^2$ and Mcfadden-Pseudo $R^2$ are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

greening all kinds of business areas, managers might derive additional private benefits from environmentally friendly projects, which further encourages them to overinvest. Consequently, firms adjust their payout policy to limit these agency problems. A one standard deviation increase in *Env* equals a 9.96 percent increase in the resources spent on dividends (*Div*). With an average partial effect of 0.0006, a one standard deviation change in *Env* amounts to a 1.71 percent points increase in the likelihood to pay dividends ($D_{Div}$).

Furthermore, we find a positive and statistically significant relationship between *Gov* with a firm's propensity to pay dividends. In line with the good governance view, well-governed firms pay special attention to the agency problem of CSR and use dividends to restrict managerial opportunism (Benlemlih, 2019; Masulis and Reza, 2015).

### 7.4.4 CSR and corporate payout: The agency-based view

Our previous results provide statistical evidence that high CSR ratings are associated with a higher dividend payout. Supported by the agency problem of free cash flow, managers can extract non-financial rents from CSR and are incentivized to overinvest. If corporate payout policy serves to control these agency problems of CSR, we would expect a greater emphasis on the disciplining mechanism and a higher propensity to pay dividends or to repurchase stocks within countries or organizational environments characterized by high susceptibility to agency issues.

This subsection further tests the implications of agency problems within CSR and the disciplining role of corporate payout. For that, we utilize the country-level anti-self-dealing index ($ASD$) of Djankov et al. (2008) to define a dummy variable ($D_{ASD}$) equal to one if a country has weak shareholder rights protection (i.e., below-median values of $ASD$) and zero otherwise.[17] In countries with weak shareholder protection, controlling shareholders can easily extract private benefits at the expense of minority shareholders, such as related party transactions or intercorporate loans (Jiang and Kim, 2020). The $ASD$ captures the protection against this expropriation of minority shareholders (Djankov et al., 2008; Jiang et al., 2010; Brockman et al., 2022) and thus, low values are indicative of agency problems.

In table 7.9, we present our logistic regression results with fixed effects. The positive and statistical significant coefficient of the interaction term between $ESG_{t-1}$ and $D_{ASD}$ in columns (1) and (3) verifies our previous results and highlights the importance of controlling agency problems of CSR via corporate payout in countries with weak shareholder protection ($D_{ASD} = 1$).[18]

### 7.4.5 Is a scandal the right time to repurchase? Evidence from a time-to-event analysis

Our analysis thus far supports the view that companies respond to the disclosure of a scandal with a reduction in stock repurchases. However, especially with regard to

[17] The anti-self-dealing index has the appealing property of being determined by the country's legal tradition, which allows an endogeneity-robust predetermined proxy for agency issues (Brockman et al., 2022).

[18] Considering the importance of the environmental pillar, demonstrated in the findings of section 7.4.3, our results remain robust if we examine the interaction between $Env_{t-1}$ and $D_{ASD}$ in columns (2) and (4).

Table 7.9: Logistic regression with fixed effects

| | *Repurchase Dummy* ($D_{Rep}$) | | *Dividend Dummy* ($D_{Div}$) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $CS_{t-1}$ | $-0.0033^{**}$ | $-0.0034^{**}$ | $-0.0013$ | $-0.0012$ |
| | (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| $ESG_{t-1}$ | $-0.0531^{***}$ | | $-0.0065$ | |
| | (0.0061) | | (0.0038) | |
| $ESG_{t-1} \times D_{ASD}$ | $0.0552^{***}$ | | $0.0233^{***}$ | |
| | (0.0061) | | (0.0040) | |
| $Env_{t-1}$ | | $-0.0273^{***}$ | | $-0.0033$ |
| | | (0.0043) | | (0.0028) |
| $Env_{t-1} \times D_{ASD}$ | | $0.0322^{***}$ | | $0.0171^{***}$ |
| | | (0.0043) | | (0.0030) |
| Controls | Yes | Yes | Yes | Yes |
| Fixed effects | Yes | Yes | Yes | Yes |
| Observations | 13,467 | 13,467 | 17,015 | 17,015 |
| Mcfadden-Pseudo $R^2$ | 0.6423 | 0.6412 | 0.7136 | 0.7138 |
| Log-Lik. | $-6353.6479$ | $-6373.6056$ | $-7758.6251$ | $-7753.6684$ |

This table presents the impact of countries with low shareholder rights protection ($D_{ASD} = 1$) on the relation between CSR and the propensity to pay dividends or to repurchase stocks, using logistic regression with year- and firm-fixed effects. Standard errors are clustered on the firm level. Columns (1) to (2) present the results for the propensity to repurchase stocks ($D_{Rep}$), and columns (3) to (4) the propensity to pay dividends ($D_{Div}$). Weak shareholder rights countries are proxied by below-median values of the anti-self-dealing index ($ASD$) of Djankov et al. (2008). A detailed description of our variables can be found in table A in the appendix. Mcfadden-Pseudo $R^2$ and the log-likelihood are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

conclusions about the market timing hypothesis, our analysis may be flawed by the use of annual data in combination with a one-year time lag between our dependent variables and our measures for corporate scandals. In this section, we address this concern and verify our results by implementing the following time-to-event analysis based on a hand-collected and international data set.

First, for firms within our sample, we collect the exact date a corporate scandal was publicly disclosed (e.g., the date of a news article discussing the issue) and the date of stock repurchase announcements from Refintiv. Since larger scandals usually result in several reports, we record each report individually, thus allowing us to account for the severity and magnitude of a scandal.

Second, we define a dummy variable $D_{Scandal}$ equal to one if the firm has a scandal in a given year and zero otherwise. We employ this dummy variable within a propensity score matching approach to pair companies from the treatment group ($D_{Scandal} = 1$) with companies from the control group ($D_{Scandal} = 0$). Following Roberts and Whited (2013) and Dehejia and Wahba (2002), we use our firm-level control variables discussed in section 7.3.3 in combination with nearest-neighbor matching and a logistic link to match treated and untreated observations within the same year and country.

Next, we determine the time-to-event variable ($Time$) for each observation in our matched sample, which is the number of days until the next repurchase announcement. Note that we need to specify a reasonable time interval to ensure that a corporate scandal can still impact the decision to announce a stock repurchase. For that, we restrict our matched sample to pairs of observations with a stock repurchase announcement within the next 3, 12, or 24 months.

Finally, we run an OLS regression with firm-level clustered standard errors and an accelerated failure time (AFT) model to determine the relation and size of the effect of $D_{Scandal}$ on $Time$.[19] In general, AFT models regress the logarithm of time-to-event data ($log(Time)$) on the covariates and thus are easy to interpret (see e.g., Wei, 1992). In addition, time-to-event data often have heavily skewed distributions and AFT models, in particular, are capable of dealing with this problem. To ensure the robustness of both models, we include the same firm-level controls used for the propensity score matching and capture further sources of unobserved heterogeneity within firm- and year-fixed effects. A positive and statistical significant coefficient for $D_{Scandal}$ would indicate an increase in the number of days until the company announces a share repurchase program.

Following the market timing hypothesis, we would expect firms to take advantage of the pricing uncertainties resulting from a scandal and quickly announce a stock repurchase in the near future (i.e., a negative coefficient for $D_{Scandal}$ and thus a shorter time-to-event). Contrarily, prolonging the time until the next repurchase announcement would support the view that managers respond to a publicly disclosed scandal with a temporal reduction of their payout activities.

Descriptive statistics for our three matched samples are displayed in table E in the appendix. Columns (1) to (3) of table 7.10 present the results for the OLS regression with fixed effects, and columns (4) to (6) for the AFT model with fixed effects. Across all settings, firms currently involved in a scandal exhibit a longer time until the next repurchase announcement. For example, the OLS regression coefficient for the paired sample with an eligible time interval of 12 months in column 2 shows that being involved in a scandal ($D_{Scandal} = 1$), ceteris paribus, prolongs the time to the next repurchase announcement by 41.56 days. Equivalently, for the AFT model in column 4, a one-unit change in $D_{Scandal}$ increases the time to the next repurchase announcement by $exp(0.3267) = 1.3863$ or by

[19] Our dummy variable $D_{Scandal}$ does not fulfill the proportional hazard assumption, and accordingly, we use the parametric approach of an AFT model, which finds common application in survival time analysis (see e.g., Wei, 1992). The AFT model requires a distributional assumption and, based on conventional selection criteria, such as log-likelihood and AIC, a Weibull distribution results in the best statistical fit.

38.63%. Note that our sample size drastically decreases for an eligible time interval of 3 months. Thus the results in columns (1) and (4) should be interpreted carefully.

Table 7.10: Time-to-event analysis

| | OLS regression with fixed-effects | | | Accelerated Failure Time (AFT) | | |
|---|---|---|---|---|---|---|
| | $Time_{3M}$ | $Time_{12M}$ | $Time_{24M}$ | $log(Time_{3M})$ | $log(Time_{12M})$ | $log(Time_{24M})$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $D_{Scandal}$ | 211.1343*** | 41.5574* | 53.0626** | 3.4426** | 0.3267*** | 0.1844*** |
| | (6.4998) | (1.8571) | (2.5478) | (2.0921) | (4.2757) | (4.7820) |
| $\text{Size}_{t-1}$ | −351.0928*** | −40.2833* | 33.5636 | −8.9042*** | −0.2411*** | 0.0557 |
| | (−4.3327) | (−1.6839) | (0.9666) | (−3.5034) | (−2.7870) | (1.5022) |
| $\text{RE}_{t-1}$ | 546.9790** | −0.0234 | −0.4013* | 18.6069*** | −0.0036** | −0.0006 |
| | (2.5675) | (−0.0627) | (−1.8658) | (3.1337) | (−2.0524) | (−0.9012) |
| $\text{AC}_{t-1}$ | 11.8690 | 51.8432 | 19.1838 | −0.6433 | 0.3279*** | 0.0757* |
| | (0.6852) | (1.4285) | (0.8570) | (−0.5508) | (3.2331) | (1.7723) |
| $\text{Cash}_{t-1}$ | 56.8356 | −183.5503 | −24.5329 | −0.7265 | −0.8846* | 0.3414 |
| | (0.3510) | (−1.3904) | (−0.1483) | (−0.1890) | (−1.8694) | (1.4460) |
| $\text{Leverage}_{t-1}$ | 1,644.7660*** | 102.0663 | 265.1984* | 32.8028*** | 0.6931 | 0.6690*** |
| | (6.7882) | (0.8761) | (1.7270) | (3.3806) | (1.5343) | (3.2069) |
| $\text{MTB}_{t-1}$ | −301.0467*** | −30.1275 | 15.4030 | −7.2843*** | −0.1064 | 0.0644** |
| | (−4.6903) | (−1.3467) | (0.7225) | (−3.4824) | (−1.2761) | (2.0314) |
| $\text{ROA}_{t-1}$ | 921.4538*** | 162.7609 | −253.1662 | 14.1759 | 0.8821* | −1.2990*** |
| | (7.5622) | (1.0390) | (−1.3705) | (1.2332) | (1.6867) | (−4.0139) |
| Constant | 2,956.3110*** | 441.4110* | 130.6378 | 81.0468*** | 5.6694*** | 5.5367*** |
| | (3.9730) | (1.6618) | (0.3611) | (3.5421) | (5.8124) | (11.7679) |
| Fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 168 | 1,772 | 4,910 | 168 | 1,772 | 4,910 |
| Adjusted $R^2$/Log-Lik. | 0.61365 | 0.2819 | 0.3651 | −1,111.23 | −9,937.94 | −30,891.65 |

This table reports the results of our time-to-event analysis for each of the three paired samples. Columns (1) to (3) present the OLS regression results, and columns (4) to (6) the results of the AFT models. We use nearest-neighbor propensity score matching with a logistic link to pair treated ($D_{Scandal} = 1$) and untreated ($D_{Scandal} = 0$) companies within the same year and country based on the firm-level control variables discussed in section 7.3.3. We restrict the eligible time-to-event for our matched observations to 3, 12, and 24 months respectively. A detailed description of our variables can be found in table A in the appendix. Adjusted $R^2$ and log-likelihood are reported upon. $*$, $**$, and $***$ indicate a 10%, 5%, and 1% level of significance, respectively.

In line with our results from previous sections, we do not find supportive evidence in favor of the market timing hypothesis. Companies may prefer to preserve their cash to cope with the scandal's consequences and delay the announcement of a stock repurchase until later. Note that this analysis relies on the announcement of a stock repurchase which, as discussed previously, does not obligate the firm to repurchase any specific amount of shares at a predetermined time. Nevertheless, this setup allows us to examine how the management plans to adapt the payout policy in response to the uncertainty caused by the scandal.

## 7.5 Conclusion

his study examines the relationship between corporate social (ir-)responsibility and a firm's payout policy by utilizing a large international sample with 7,260 distinct publicly listed firms over the period 2003 to 2021. We contribute to the literature by analyzing dividends and stock repurchases in the context of both CSR and CSI in an international sample, thereby, to the best of our knowledge, filling the academic void regarding research on how irresponsible corporate behavior (i.e., corporate scandals) is linked to a firm's payout policy.

Our panel models show robust evidence that high CSR ratings are associated with a statistically significant increase in the likelihood that a firm pays dividends and that companies with high CSR ratings spend more financial resources on dividends. In particular, firms with superior environmental performance and firms within countries susceptible to agency problems tend to attach more importance to their payout. Our results highlight that social irresponsible firms engage in fewer stock repurchases and spend less on dividends but are still reluctant to forego dividends altogether. Furthermore, we show that for a sample of pair-matched firms, being involved in a scandal is positively related to the number of days until the announcement of a stock repurchase. Our results are robust to alternative measures of CSR and CSI.

In sum, these findings provide challenging implications for the signaling mechanism of corporate payout in the context of CSR. As CSR disclosure and ESG ratings reduce information asymmetries (Dhaliwal et al., 2011; Cheng et al., 2014a), firms with good ratings would benefit less from the signaling mechanism of payout. Instead, our findings support the strand of literature regarding the agency problem of free cash flow (Easterbrook, 1984; Jensen, 1986). Given the omnipresent trend toward sustainability, it seems more important than ever for companies to implement an appropriate payout policy that limits managers' incentives to overinvest in CSR.

Moreover, our results contrast the market timing theory for stock repurchases and instead align with the literature on precautionary cash holding (Bates et al., 2009; Almeida et al., 2004; Han and Qiu, 2007; Bolton et al., 2013). While it may seem reasonable for the company to take advantage of pricing inefficiencies after a scandal to buy back shares at a relatively low price, investors should keep in mind that companies prefer to retain their cash to guarantee future investments rather than timing their repurchases. Overall the results show that unethical behavior reduces cash flows to investors through every payout channel.

Although the corporate payout puzzle is far from being solved, our results highlight the importance of CSI and CSR in a firm's payout decision. In addition, the continuous evolution of CSR reporting standards, while simultaneously fostering the disclosure of unethical corporate behavior, remains a critical task to credibly capture the sustainable and ethical orientation of a firm. In light of the rising social and academic interest in corporate social (ir-)responsibility and the evolution in corporate payout policy, the interaction between these trends deserves further attention in the future.

# Appendix

Table A.1: Description of variables (Part 1)

| | |
|---|---|
| **Dependent variables:** | |
| Stock Repurchases (*Rep*) | The logarithm of 1 plus the expenditures on the purchase of common and preferred stocks (Item 115) minus the change (first difference) in preferred stock reduction (Item 10) (see Hong et al., 2012). Missing values for non-US firms are substituted with the corresponding values from Thomson Reuters Datastream. |
| Repurchase Dummy ($D_{Rep}$) | A dummy variable equal to one if the firm has repurchased stocks (i.e., $Rep > 0$). |
| Dividends (*Div*) | The logarithm of 1 plus cash dividends on common stocks (Item 21). |
| Dividend Dummy ($D_{Div}$) | A dummy variable equal to one if the firm pays out cash dividends on common stocks (i.e., $Div > 0$). |
| **Measurement of CSR and CSI:** | |
| Rescaled Controversies Score (*CS*) | The ranking of a company's (un-)ethical behavior (on a scale of 0 to 100) relative to its peer group, based on 23 CSR-related controversy topics. The score accounts for news about unethical business practices from global media sources (such as Bloomberg, Reuters News, or LexisNexis), NGOs (such as Greenpeace or Amnesty International), and company reports (Refinitiv, 2022). Due to the rescaling, firms without any scandal in a fiscal year will receive a score of 0. An increase in the number of scandals will increase the *Controversy Score*. |
| ESG Score (*ESG*) | The ranking of a company's environmental (E), social (S), and corporate governance (G) performance (on a scale of 0 to 100) relative to its peer group (Refinitiv, 2022). |
| **Firm-level control variables:** | |
| Size (*Size*) | The logarithm of 1 plus total assets (Item 6). |
| Retained Earnings (*RE*) | The ratio of payout-adjusted retained earnings (Item 36 + Item 21 + Item 19) to the book value of equity (Item 60 + 74) (see e.g., Denis and Osobov, 2008; De Cesari and Ozkan, 2015). |
| Analyst Coverage (*AC*) | Logarithm of 1 plus the number of analysts providing earnings forecasts for the firm as captured by I/B/E/S. Missing values are set to 0 (Blankespoor et al., 2014; Bhattacharya and Jacobsen, 2016). |
| Cash Ratio (*Cash*) | The ratio of cash and short-term investments (Item 1) to total assets (Item 6). |
| Leverage (*Lev*) | The ratio of total long-term debt (Item 9) to total assets (Item 6). |
| Market-to-Book (*MTB*) | The logarithm of 1 plus the market value of a firm's equity divided by the book value of equity. The market value of equity is calculated as the product of market prices at the calendar year-end times the number of shares outstanding (Item 25). Closing prices for US firms come from CRSP and for non-us firms from Datastream. The book value of equity is defined as the total common and ordinary equity (Item 60) plus deferred taxes balance sheet (Item 74) (see Baker et al., 2003). |
| Return on Assets (*ROA*) | The ratio of operating income before depreciation (Item 13) to total assets (Item 6) (see Farre-Mensa and Ljungqvist, 2016). |

Table A.2: Description of variables (Part 2)

| | |
|---|---|
| **Additional measures of CSR and CSI:** | |
| Number of Scandals (*NoS*) | The annual aggregated count of publicly disclosed news about unethical business practices within 23 CSR-related topics for a given year. These topics include, for example, excessive environmental pollution, child labor, diversity issues, tax or accounting frauds, and shareholder rights infringements. Refinitiv captures publicly disclosed news about unethical business practices from global media sources, NGOs, and company reports (Refinitiv, 2022). |
| Environmental Score (*Env*) | The ranking of a company's environmental performance (on a scale of 0 to 100) relative to its peer group and measures the company's efforts to reduce environmental pollution and resource waste or to support green innovations (Refinitiv, 2022). |
| Social Score (*Soc*) | The ranking of a company's social performance (on a scale of 0 to 100) relative to its peer group. This score measures aspects of employee diversity and fair working conditions, product safety, and actions to protect data privacy or to prevent child labor (Refinitiv, 2022). |
| Governance Score (*Gov*) | The ranking of a company's governance performance (on a scale of 0 to 100) relative to its peer group. This score covers the company's willingness to establish a stable CSR policy and transparent CSR reporting, as well as its efforts for fair management compensation and shareholder rights protection (Refinitiv, 2022). |
| **Anti-self-dealing:** | |
| Anti-self-dealing Dummy ($D_{ASD}$) | A dummy variable equal to one if the anti-self-dealing index for a given country exceeds the sample median and zero otherwise. The anti-self-dealing index is a time-invariant variable and is obtained from Andrei Shleifer's website. |
| **Time-to-event analysis:** | |
| Time-to-event ($Time$) | The number of days until the firm announces a stock repurchase. |
| Scandal Dummy ($D_{Scandal}$) | A dummy variable equal to one if the firm has a scandal in a given year. |

This table presents a detailed explanation of our employed variables. Data on financial statements are obtained from Compustat (with the corresponding data item mentioned in parentheses). Share prices for US firms are from CRSP and for non-US firms from Thomson Reuters Datastream. CSR- and CSI-related data, as well as the date of a stock repurchase announcement, are obtained from Refinitiv. The anti-self-dealing index is available on Andrei Shleifer's website.

Table A.3: Firm distribution by country.

| Country | N | Freq. |
|---|---|---|
| USA | 2,643 | 36.40% |
| China | 690 | 9.50% |
| Great Britan | 482 | 6.64% |
| Australia | 397 | 5.47% |
| Japan | 390 | 5.37% |
| Sweden | 212 | 2.92% |
| Germany | 182 | 2.51% |
| Canada | 146 | 2.01% |
| Taiwan | 144 | 1.98% |
| France | 133 | 1.83% |
| Korea | 130 | 1.79% |
| Switzerland | 128 | 1.76% |
| India | 116 | 1.60% |
| Hong Kong | 109 | 1.50% |
| South Africa | 108 | 1.49% |
| Brazil | 77 | 1.06% |
| Italy | 76 | 1.05% |
| Netherlands | 63 | 0.87% |
| Finland | 63 | 0.87% |
| Thailand | 60 | 0.83% |
| Others | 911 | 12.55% |
| Total | 7,260 | 100% |

This table presents the number of firms (N) and their fraction of the total sample (Freq.) per country. For country identification, we use the ISO Country Code from Compustat.

Table A.4: Logistic regression with fixed effects - Excluding US

| | *Repurchase Dummy* ($D_{Rep}$) | | *Dividend Dummy* ($D_{Div}$) | |
|---|---|---|---|---|
| | US-only | Excluded | US-only | Excluded |
| | (1) | (2) | (3) | (4) |
| $CS_{t-1}$ | $-0.0040^{**}$ | $-0.0019$ | $0.0009$ | $-0.0029^{*}$ |
| | (0.0014) | (0.0016) | (0.0022) | (0.0013) |
| $ESG_{t-1}$ | $-0.0061$ | $-0.0093^{*}$ | $0.0337^{***}$ | $0.0073^{**}$ |
| | (0.0037) | (0.0043) | (0.0057) | (0.0028) |
| $Size_{t-1}$ | $0.5566^{***}$ | $0.4715^{***}$ | $1.4450^{***}$ | $0.6646^{***}$ |
| | (0.0931) | (0.0982) | (0.1557) | (0.0737) |
| $RE_{t-1}$ | $-0.0477$ | $-0.1127$ | $0.3310^{***}$ | $0.7075^{***}$ |
| | (0.0317) | (0.0785) | (0.0576) | (0.1825) |
| $AC_{t-1}$ | $0.1461$ | $-0.0443$ | $0.2225$ | $0.3892^{***}$ |
| | (0.0990) | (0.0857) | (0.1553) | (0.0607) |
| $Cash_{t-1}$ | $0.7614$ | $1.1544$ | $1.5262^{*}$ | $0.4564$ |
| | (0.4602) | (0.6170) | (0.7421) | (0.3904) |
| $Lev_{t-1}$ | $-2.9635^{***}$ | $-1.5244^{**}$ | $-2.6046^{***}$ | $-1.9580^{***}$ |
| | (0.3781) | (0.5198) | (0.5924) | (0.3201) |
| $MTB_{t-1}$ | $0.0758$ | $-0.0011$ | $0.2637$ | $0.2052^{**}$ |
| | (0.0927) | (0.1022) | (0.1438) | (0.0646) |
| $ROA_{t-1}$ | $4.7847^{***}$ | $4.5091^{***}$ | $11.4574^{***}$ | $7.0237^{***}$ |
| | (0.5664) | (0.8121) | (1.1443) | (0.5216) |
| Fixed effects | Yes | Yes | Yes | Yes |
| Observations | 7,990 | 5,597 | 3,577 | 13,693 |
| Macfadden-Pseudo $R^2$ | 0.6053 | 0.7296 | 0.8672 | 0.6887 |
| Log Lik. | $-3631.5624$ | $-2649.2284$ | $-1407.3143$ | $-6172.3709$ |

This table presents the logistic regression results with year- and firm-fixed effects separately for a US-only and a sample without US. Standard errors are clustered on the firm level. Columns (1) and (3) present the results for the propensity to repurchase stocks ($D_{Rep}$) and pay dividends ($D_{Rep}$) for companies located in the US, and columns (2) and (4) exclude the US. A detailed description of our variables can be found in table A.1 in the appendix. Note that the fixed-effects logistic regression requires variation in the binary dependent variable ($D_{Rep}$ or $D_{Div}$), i.e. the firm has to change from a payer (repurchaser) to a non-payer (non-repurchaser) or vice versa at a given point in time, which reduces our sample size. Mcfadden-Pseudo $R^2$ and the log-likelihood are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

Table A.5: Logistic regression with fixed effects - Excluding Manufacturing

| | *Repurchase Dummy* ($D_{Rep}$) | | *Dividend Dummy* ($D_{Div}$) | |
|---|---|---|---|---|
| | Manufacturing-only | Excluded | Manufacturing-only | Excluded |
| | (1) | (2) | (3) | (4) |
| $CS_{t-1}$ | $-0.0032^{*}$ | $-0.0036^{*}$ | $-0.0023$ | $-0.0005$ |
| | (0.0015) | (0.0015) | (0.0015) | (0.0015) |
| $ESG_{t-1}$ | $-0.0056$ | $-0.0042$ | $0.0117^{***}$ | $0.0073^{*}$ |
| | (0.0038) | (0.0039) | (0.0035) | (0.0033) |
| $Size_{t-1}$ | $0.6425^{***}$ | $0.5705^{***}$ | $0.7835^{***}$ | $0.8424^{***}$ |
| | (0.0976) | (0.0898) | (0.0983) | (0.0852) |
| $RE_{t-1}$ | $-0.1131^{**}$ | 0.0126 | $0.2368^{**}$ | $0.8127^{***}$ |
| | (0.0360) | (0.0463) | (0.0738) | (0.1249) |
| $AC_{t-1}$ | $-0.0457$ | 0.1003 | $0.3456^{***}$ | $0.2982^{***}$ |
| | (0.0975) | (0.0850) | (0.0826) | (0.0744) |
| $Cash_{t-1}$ | 0.8235 | 1.0332 | $1.9434^{***}$ | $-0.3882$ |
| | (0.4898) | (0.5397) | (0.5128) | (0.4404) |
| $Lev_{t-1}$ | $-2.5535^{***}$ | $-1.4140^{***}$ | 0.0248 | $-2.0207^{***}$ |
| | (0.4363) | (0.4062) | (0.4316) | (0.3466) |
| $MTB_{t-1}$ | 0.0858 | 0.0430 | $-0.2279^{**}$ | $0.4637^{***}$ |
| | (0.0910) | (0.0990) | (0.0847) | (0.0793) |
| $ROA_{t-1}$ | $5.9722^{***}$ | $4.2212^{***}$ | $10.6745^{***}$ | $6.6218^{***}$ |
| | (0.6393) | (0.6685) | (0.8023) | (0.5631) |
| Fixed effects | Yes | Yes | Yes | Yes |
| Observations | $6,813$ | $6,774$ | $7,910$ | $9,360$ |
| Macfadden-Pseudo $R^2$ | 0.7833 | 0.7767 | 0.7602 | 0.7338 |
| Log Like. | $-3206.6055$ | $-3237.5993$ | $-3628.6486$ | $-4208.5268$ |

This table presents the logistic regression results with year- and firm-fixed effects separately for manufacturing-only and without manufacturing. Standard errors are clustered on the firm level. Columns (1) and (3) present the results for the propensity to repurchase stocks ($D_{Rep}$) and pay dividends ($D_{Div}$) for companies in the manufacturing sector, and columns (2) and (4) exclude the manufacturing industry. A detailed description of our variables can be found in table A.1 in the appendix. Note that the fixed-effects logistic regression requires variation in the binary dependent variable ($D_{Rep}$ or $D_{Div}$), i.e. the firm has to change from a payer (repurchaser) to a non-payer (non-repurchaser) or vice versa at a given point in time, which reduces our sample size. Mcfadden-Pseudo R2 and the log-likelihood are reported upon. t-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

Table A.6: Paired Sample characteristics

| Statistic | N | Min | Median | Max | Mean | St. Dev. |
|---|---|---|---|---|---|---|
| $Time_{3M}$ | 168 | 3 | 42 | 89 | 43.19 | 23.55 |
| $Time_{12M}$ | 1,772 | 3 | 168 | 365 | 172.89 | 99.85 |
| $Time_{24M}$ | 4,910 | 3 | 287 | 729 | 305.01 | 188.69 |

This table reports descriptive statistics (number of observations, minimum, median, maximum, mean, and standard deviation) about the time-to-event variable ($Time$) for our paired samples. We use nearest-neighbor propensity score matching with a logistic link to pair treated ($D_{Scandal} = 1$) and untreated ($D_{Scandal} = 0$) companies within the same year and country based on the firm-level control variables discussed in section 7.3.3. We restrict the eligible time-to-event for our matched observations to 3, 12, and 24 months respectively. A detailed description of our variables can be found in table A.1 in the appendix.

# Chapter 8

# The Good Left Undone: About future scandals, past returns, and ineffectual ESG

This chapter is based on a joint work with Christian Sparrer (University of Regensburg).

**Abstract** A worldwide sample of 10,500 public companies from 2002 to 2022 exemplifies that excess returns can predict future unethical behavior and corporate scandals. In line with market efficiency, statistical evidence shows that excess returns are a statistical precursor of corporate scandals, while the disclosure of unethical behavior does not affect long-term outperformance. This study sheds light on the potential for scandals to be a more tangible measure than the ESG score, which can be biased by greenwashing and even has a positive relationship with the number of scandals in our sample. Our results highlight that stakeholders should position themselves carefully within the counterintuitive relationship of excess returns, scandals, and sustainability ratings.

**Keywords** Corporate Scandals, Sustainability, ESG, Asset Pricing

**JEL** G10, M14

## 8.1 Introduction and Related Literature

In a world of efficient capital markets, investors are aware of the necessity to price new information and seek to value the future by demanding returns and risk premia. At the same time, the awareness of capital markets, institutional investors, and society as a whole towards a sustainable economy and a green future is omnipresent.[1] While the greenness of investments or a company, in general, can be concealed or distorted by greenwashing (Laufer, 2003; Delmas and Burbano, 2011), corporate scandals cannot be hidden forever from the public because of their severity. Besides the reputational consequences for the company, corporate scandals can also inflict severe damage on the environment or society.[2]

This paper shifts the academic focus towards corporate scandals and unravels the dynamic relationship between returns and scandals by stringently following the chain of thought of pricing information and efficient capital markets.[3] Our statistical results strongly support the view that past excess returns are a precursor for future risk in terms of scandals and unethical behavior.

Rising public awareness regarding sustainability sparked an ongoing academic debate about the relationship between corporate social responsibility (CSR) and corporate financial performance (CFP) (Friede et al., 2015). Hereby, the discussion is mainly centered around a forward impact, i.e. that past or present CSR affects future financial performance. Despite the magnitude of research dedicated to this topic, the results remain inconsistent to date, with three distinct viewpoints emerging.

The first one, often referred to as the *doing good while doing well* hypothesis, indicates a positive relation between high CSR and financial performance (see e.g. Kempf and Osthoff, 2007; Statman and Glushkov, 2009; Waddock and Graves, 1997; Bénabou and Tirole, 2010; Edmans, 2011). Myopic managers favor decisions that improve current earnings rather than long-term value. Short-term-oriented investors are unwilling to price any potential long-term benefits of CSR (Derwall et al., 2005; Edmans, 2011; Bénabou and Tirole, 2010) and undervalue companies that engage in sustainability. The second one, the *doing good but not well* hypothesis, reports a negative relationship (see e.g. Barnea and Rubin, 2010; Renneboog et al., 2008; Hong and Kacperczyk, 2009; Bolton and Kacperczyk,

[1]The total US-domiciled assets under management that incorporate corporate social responsibility increased from 12.0$ trillion in 2018 to 17.1$ trillion in 2020. This represents nearly 1 in 3 dollars of total US assets under professional management spent according to sustainable criteria. See Report on Sustainable and Responsible Investing Trends by the Forum for Sustainable and Responsible Investment, 2020.

[2]A prominent example demonstrating the encompassing consequences of scandals is the company BP. The company has been sued multiple times after the Deepwater Horizon oil spill in 2010, and besides the immense damage to the environment and wildlife, this corporate scandal left thousands of workers temporarily unemployed.

[3]In line with literature on media scandals (see e.g., Thompson, 2005), we define corporate scandals as unethical corporate behavior that got disclosed to the broader society through, for example, different media channels or NGO reports.

2021). Consistent with the trade-off theory (Aupperle et al., 1985), some researchers argue that high expenditures on CSR are seen as a waste of precious financial resources that could otherwise be spent more efficiently (see e.g. Barnea and Rubin, 2010; Aouadi and Marsat, 2018; Krüger, 2015). Others emphasize the risk-mitigation view and a reduction in information asymmetry for high CSR firms, which decreases companies' cost of equity (Sharfman and Fernando, 2008; El Ghoul et al., 2011; Dhaliwal et al., 2011) or debt (Goss and Roberts, 2011). Finally, the last view suggests no clear positive or negative relationship (see e.g. Hamilton et al., 1993; Auer and Schuhmacher, 2016), because the benefits of CSR might be offset by their costs.

Other researchers reverse this relationship but do not find a consistent conclusion either. Waddock and Graves (1997) and Ioannou and Serafeim (2012) note that high CSR ratings are associated with good prior financial performance (i.e. slack resource theory). In contrast, Shackleton et al. (2021) show that firms try to offset weak prior financial performance with an improvement in future CSR and thus provide statistical evidence in favor of a negative and reverse causal relationship. However, these studies and, consequently, their results are not easily comparable with each other. First, they target different geographical areas, such as the U.S. market (Van der Laan et al., 2008), the EU market (Qiu et al., 2016), or an international sample (Auer, 2016). Second, they focus either on accounting-based (Mervelskemper and Streit, 2017) or on stock market-based measures of financial performance (Kempf and Osthoff, 2007; Aouadi and Marsat, 2018). Finally, recent literature emphasizes the lack of a standardized definition of CSR or a homogeneous measure of CSR (Chatterji et al., 2016; Dorfleitner et al., 2015), while others criticize the black-box nature of environmental, social, and corporate governance (ESG) ratings (Berg et al., 2020) and their inability to address greenwashing adequately. In consequence, the conflicting academic results are mainly data-driven (Capelle-Blancard and Monjon, 2012; Revelli and Viviani, 2015).

In this study, we alleviate the concerns mentioned above regarding ESG ratings in an asset pricing context, as we do not focus on aggregated ESG ratings but instead shift our attention toward the dynamic relation of returns and publicly disclosed CSR-related corporate scandals in a worldwide sample. Different sources, such as international NGOs, the media, or other stakeholders, publicly disclose, and validate information about corporate misconduct. Because the company cannot alter the societal perception of disclosed scandals so easily, corporate scandals are more tangible, less susceptible to interpretation and measurement biases than CSR, and evade the black-box nature of ESG ratings.

Prior literature addresses corporate scandals in the context of a corrupt business environment (Rodriguez et al., 2005; Oliver, 1991), analyzes their interaction with CSR (Godfrey, 2005), or discusses the relation between CSR and corporate scandals through the moderating role of a country's legal origin (Liang and Renneboog, 2017). Others focus on the relation between corporate scandals and firm value (Aouadi and Marsat, 2018), discuss how the visibility of corporate scandals affects financial risk (Kölbel et al., 2017), or provide a more general overview of different country- and firm-level drivers of corporate scandals (Dorfleitner et al., 2022).

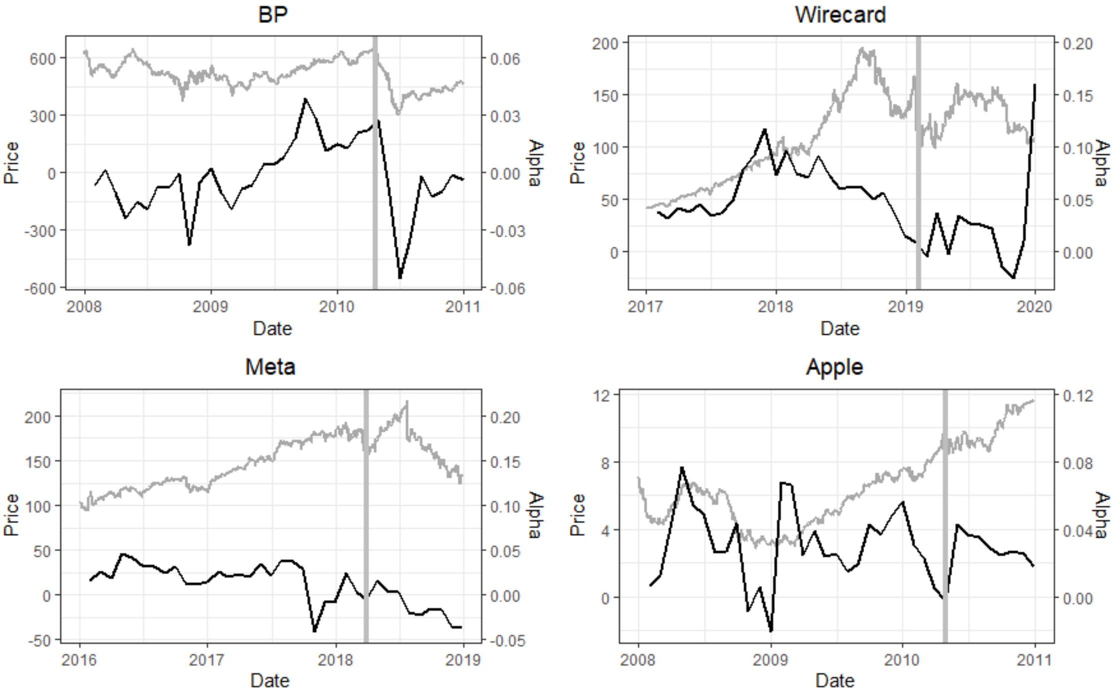
This paper contributes to the literature in various ways. First, we question the traditional temporal direction regarding current ethical and sustainable behavior and future financial performance. We analyze corporate scandals and realized returns of a worldwide sample of roughly 10,500 public companies and find statistical evidence that excess returns, measured in alphas in terms of the classic Fama and French (2015) five-factor model, indicate future corporate scandals. Our multitude of statistical models strongly suggest a reverse impact (prior returns predicting future scandals) rather than a forward impact (prior scandals predicting future returns). To further motivate the topic, Figure 8.1 illustrates the relationship between excess returns and corporate scandals developed in this study for selected well-known examples of corporate misconduct. In all cases, the media reports and allegations of misconduct occurred before the public admission of corporate wrongdoing. If the market efficiency hypothesis also applies to scandals, it should be possible to establish a link between returns and corporate scandals. Namely, that excess returns in the form of alpha may indicate future corporate misconduct.

Most importantly, all of our findings are strictly controlled for the sustainability of the corresponding company in terms of ESG scores. In addition, we show that the environmental (E) and governance (G) components of the ESG score moderate the reverse relation between returns and scandals in a counterintuitive relation because the reverse impact only persists within well-governed firms or firms deemed environmentally friendly.

The implications of this paper are as follows: Excess returns, sustainability measured in ESG ratings, and corporate scandals interact in a counterintuitive relationship with each other. When investors, regulators, and academics alike rely solely on ESG ratings, they overlook the corporate misconduct component. Because outperformance in the past and high ESG ratings are more likely to attract investors' attention than deter it, unaware investors are more likely to engage in corporate misconduct inadvertently. This is even more problematic as corporate scandals in our sample do not have a statistically significant impact on the ability to outperform in the long run. The results also imply that while not every outperformance is related to a scandal, the connection can be used as another screening criterion for asset management in terms of corporate behavior and sustainability.

The remainder of the paper is organized as follows: In Section 8.2, we develop our theoretical reasoning. Section 8.3 describes our data and reports descriptive statistics. Section 8.4 presents our methodology. In Section 8.5, we discuss our baseline results, address potential limitations through several robustness checks, and show the economic significance of our results. Finally, in Section 8.6, we conclude the study.

Figure 8.1: Stock prices, excess returns, and corporate scandals: anecdotal evidence.




This figure illustrates anecdotal evidence of the interaction between stock prices and monthly excess returns in the context of some well-known corporate scandals. The left y-axis is associated with stock prices, represented by the color gray, while the right axis depicts monthly excess returns, represented by the alpha of the five-factor model, in black. The chart shows major events such as the BP Deepwater Horizon disaster on April 22, 2010, the Wirecard police investigation in Singapore on February 18, 2018, the Facebook (now Meta) Cambridge Analytica scandal on March 25, 2018, and the disclosure of suicides at Apple's Foxconn factory starting in May 2010, delineated by vertical gray lines. In all cases, major news sources such as the Financial Times and the Wall Street Journal reported significant wrongdoings before the disclosures.

## 8.2 Theoretical Development

Unethical corporate behavior, such as cutting costs at the expense of environmental, product, or workplace safety, exploiting one's workforce through forced overtime, and even tax or accounting frauds, can lead to competitive advantages and increased returns in the short-term. Simultaneously, the disclosure of these unethical practices may have severe reputational consequences for the company and can affect short-term stock returns (Krüger, 2015).

In the sense of efficient capital markets (Fama, 1965; Fama, 1970) as well as in the sense of a Grossman and Stiglitz (1976) world, investors actively seek to obtain any relevant information and price them accordingly in their risk premia. Contrary to these efforts, companies actively try to impede the distribution of negative news and the disclosure of their own unethical behavior, which challenges the assumption of information-efficient markets (Carberry et al., 2018; Schreck and Raithel, 2018). Thus the classical cause-effect relationship of first having a public scandal and consequently dropping prices and returns is highly questionable. This entails the question of whether the demanded risk premia or expected returns are one result (forward impact) or rather one potential predictor (reverse impact) of unethical behavior and corporate scandals. However, studies regarding the reverse mechanisms and the potential causality between past financial performance and future corporate scandals are to our best knowledge lacking in the literature.

In this paper, we explore the dynamic relation between excess returns (which come from shareholders' attempt to efficiently price risks and premia in anticipation of future behavior) and corporate scandals. By withholding negative news, companies create information asymmetries between themselves and their stakeholders, which distorts the optimal risk premium of a company. Because investors are aware of these concealment measures to some degree, they obviously seek compensation for their risks taken and demand higher risk premia. Since the standard factor models in asset pricing are not constructed to represent this possible connection, the likelihood of the occurrence of a corporate scandal should be found in the unexplained component of excess returns, if there is any relationship at all. Following the chain of thought of pricing risks within efficient capital markets, we hypothesize that excess returns are a statistical precursor of future scandals.

***Hypothesis I):*** *The past realization of excess returns is a statistical precursor for future corporate scandals.*

## 8.3 Data & Summary Statistics

### 8.3.1 Measurement of CSR-related scandals

In line with the literature (see e.g., Dorfleitner et al., 2022; Thompson, 2005), this study defines corporate scandals as unethical corporate behavior in terms of environmental, social, or corporate governance issues that were exposed to the public.[4] Importantly, for our definition of a corporate scandal, we require both the actual unethical behavior of the company and its disclosure to the broader society because stakeholders can only react to publicly known issues (Aouadi and Marsat, 2018; Weick et al., 2005).

Since we are well aware of the current and justified criticism of the black-box nature and rewriting of past ESG ratings mentioned by Berg et al. (2020), we restrain from employing aggregated CSI scores but instead use the total numeric count of corporate scandals (*Number of Scandals*) a company is involved in a given year. Within this variable, we consider the number of publicly disclosed CSR-related scandals for 23 distinct topics, such as excessive environmental pollution, employee- or customer-related issues, or shareholder

[4] Note that corporate misconduct is not always an illegal action (Godfrey, 2005).

rights infringements. Using a raw count of scandals also allows us to account for the severity and magnitude of a scandal. Larger scandals usually involve different scandal topics and news sources, which is reflected in a higher count per year. Furthermore, most major scandals are accompanied by lengthy legal proceedings, so these scandals will continue to be considered in subsequent years, as long as they remain present in the media. Media attention and reports change investors' perception of a company and can alter the behavior of both, investors and companies, as pointed out by Gantchev et al. (2022).

Since 2002, Refinitiv captures negative CSR-related news from global media sources (such as Bloomberg, Reuters News, Financial Times, or LexisNexis), NGO websites (e.g., Amnesty International or Greenpeace), or directly from company reports, which results in one of today's largest and most transparent international CSR-related data sets (see Cheng et al., 2014a; Durand and Jacqueminet, 2015).

### 8.3.2 Measurement of excess returns

In order to evaluate a firm's financial performance and to determine the annualized excess return (*Alpha*), we use the five-factor model with the following equation (Fama and French, 2015):

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$

for a non-overlapping twelve-month return window. The intercept $a_i$ denotes the monthly risk-adjusted outperformance of firm $i$, $R_{it}$ is the individual firm return, and $R_{Ft}$ represents the risk-free return. $R_{Mt} - R_{Ft}$ is the excess return of the market portfolio, $SMB_t$ is the return of small stocks minus big stocks in terms of market capitalization, and $HML_t$ is the high-minus-low factor regarding the book-to-market value. $RMW_t$ describes the difference in returns between stocks with robust and weak profitability, while $CMA_t$ denotes the differences in returns between high-investment companies (i.e. aggressive) and low-investment companies (i.e. conservative). The estimated regression coefficients are $b_i$, $s_i$, $h_i$, $r_i$, and $c_i$, whereas $e_{it}$ denotes the zero-mean residual. If all variation in expected returns is captured by the factors, the intercept and, consequently, the risk-adjusted outperformance of the company is zero. We derive *Alpha* by annualizing the intercept $a_i$.

### 8.3.3 Further independent firm-level variables

We need to control for various firm-level variables, which may distort the relationship between financial performance and corporate scandals.

To account for the well-discussed link between CSR and financial performance (see section 8.1), we add the *ESG Score* by Refinitiv, which measures a company's environmental, social, and corporate governance performance relative to its respective peer industry group on a scale of 0 to 100. Firms with high values are considered more sustainable than those within the same peer group with a lower score.

As larger and more visible firms tend to be exposed to greater public scrutiny (Drempetic et al., 2019; Schreck and Raithel, 2018; Fiss and Zajac, 2006), corporate scandals can be detected more easily. We account for this and include *Size*, which is the natural logarithm of total assets at the end of year $t$, as well as the number of analysts who provide an earnings forecast for the company (*Analyst Coverage*).

Jensen (1986) describes another important disciplining effect on corporate behavior caused by debt obligations. Companies with high leverage are monitored more closely by capital lenders (see e.g. Harris and Raviv, 1990), which, in turn, restricts the ability of companies to behave unethically. On the other hand, companies with sufficient financial resources can withstand external pressure more easily. We capture these effects with the variables *Leverage*, which depicts the ratio of total debt to total assets, and *Cash*, which is the ratio of cash and short-term investments to total assets.

Finally, we add the natural logarithm of the book-to-market value of a company $i$ in the year $t$ (*Book-to-Market*), as well as a standardized measure for unanticipated earnings surprises (*EPS Surprises*).

A detailed description of all variables can be found in Table A.1 in the appendix. We obtain all data from Thomson Reuters Datastream. All variables (except for the *Number of Scandals* and the *ESG Score*) are winsorized at the 5% and 95% level for each industry sector and year.[5]

### 8.3.4 Summary Statistics

The variable of interest (i.e., the *Number of Scandals*) is available from 2002 to 2022 and includes 10,522 public companies from 67 countries. The resulting unbalanced panel data set comprises a maximum of 137,791 annual observations, although not all observations are taken into account due to missing data. Summary statistics for the full sample are displayed in Table 8.1. The mean *Number of Scandals* is 0.21, with a standard deviation of 1.42. In conjunction with a median of 0 and a skewness of $-2.82$, the *Number of Scandals* variable shows that most of the companies are not involved in a scandal.[6] Furthermore, in the case of *Alpha*, it should be noted that it is a global and, therefore, very large sample, containing not only traditional stocks but also many small companies for which the five-factor model does not always provide a good fit. Thus, the average is biased upward by outliers in the

[5] Using a 1% cut-off value is not sufficient to remove statistical outliers from small sample sizes per industry-year combination.

[6] This type of distribution, which is unfavorable for linear regression designs, is addressed in section 8.4.

summary statistics, while the median shows a correct pattern. To ensure that the results are not affected by these outliers, we use several approaches to limit the high maxima in excess returns. First, we utilize *Alpha*$^{Win}$ winsorized at stricter levels of 10% and 90%. For *Alpha*$^{IR}$, we remove observations of *Alpha* that exceed two times the interquartile range. Additionally, we vary the method used to derive *Alpha* and calculate *Alpha*$^{MM}$ as the annualized intercept in the following market model based on a non-overlapping twelve-month return window:

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + e_{it}$$

Panel A of Table 8.2 presents the distribution of observations across industry sectors, and Panel B across continents. For the industry classification, we use the Refinitiv Business Classification. Due to the small sample size, we exclude the sector *Academic & Educational Services.*

Table 8.3 reports the correlation matrix. In line with the literature, we find a positive correlation (0.43) between *Size* and *ESG Score* (see e.g., Drempetic et al., 2019). Furthermore, the positive correlation (0.20) between the *Number of Scandals* and the *ESG Score* already hints at a possible counterintuitive relation between acting sustainable and ethical.

Table 8.1: Descriptive statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|---|
| *Dependent Variables* | | | | | | | | |
| Number of Scandals | 137,791 | 0.21 | 1.42 | 0 | 0 | 0 | 0 | 109 |
| Alpha | 137,791 | 0.34 | 1.64 | −0.98 | −0.25 | 0.05 | 0.47 | 62.41 |
| Alpha$^{Win}$ | 137,791 | 0.19 | 0.65 | −0.75 | −0.25 | 0.05 | 0.47 | 3.42 |
| Alpha$^{IR}$ | 127,258 | 0.07 | 0.49 | −0.98 | −0.28 | 0.01 | 0.34 | 1.50 |
| Alpha$^{MM}$ | 137,791 | 0.18 | 0.67 | −0.91 | −0.15 | 0.06 | 0.33 | 18.56 |
| *Further Variables* | | | | | | | | |
| ESG Score | 73,985 | 41.29 | 20.36 | 0.14 | 24.99 | 39.09 | 56.45 | 95.19 |
| Analyst Coverage | 137,791 | 7.76 | 7.58 | 0 | 2 | 6 | 12 | 56 |
| Size | 137,791 | 14.46 | 1.92 | 8.16 | 13.15 | 14.46 | 15.76 | 20.12 |
| Cash | 122,963 | 0.16 | 0.17 | 0.00 | 0.04 | 0.10 | 0.22 | 0.97 |
| Leverage | 137,701 | 0.23 | 0.18 | 0.00 | 0.07 | 0.21 | 0.36 | 0.74 |
| Book-to-Market | 137,791 | −0.60 | 0.77 | −2.89 | −1.10 | −0.55 | −0.07 | 3.51 |
| EPS Surprises | 94,152 | 0.38 | 2.10 | −10.75 | −0.74 | 0.23 | 1.31 | 18.31 |

This table reports the descriptive statistics for the full sample. The sample includes 10,522 distinct firms from 2002 to 2022. All variables (except for the *Number of Scandals* and the *ESG Score*) are winsorized at the 5% and 95% level for each industry sector and year. For robustness purposes, we apply several adjustments to *Alpha*. First, *Alpha*$^{Win}$ is winsorized at the 10% and 90% level. For *Alpha*$^{IR}$, we remove all observations that exceed twice the interquartile range, and *Alpha*$^{MM}$ is the annualized intercept of the market model based on a non-overlapping twelve-month return window.

Table 8.2: Sample characteristics

**Panel A.** Sample distribution by industry sectors.

| Refinitiv Business Classification | N | Freq. |
|---|---|---|
| Academic & Educational Services | 46 | 0.45% |
| Basic Materials | 968 | 9.19% |
| Consumer Cyclicals | 1,393 | 13.24% |
| Consumer Non-Cyclicals | 723 | 6.87% |
| Energy | 647 | 6.15% |
| Financials | 1,598 | 15.19% |
| Healthcare | 1,141 | 10.84% |
| Industrials | 1,500 | 14.25% |
| Real Estate | 749 | 7.12% |
| Technology | 1,392 | 13.23% |
| Utilities | 365 | 3.47% |
| **Total** | 10,522 | 100% |

**Panel B.** Sample distribution by continents.

| Continent | N | Freq. |
|---|---|---|
| Africa | 177 | 1.68% |
| Asia | 2,667 | 25.35% |
| Europe | 2,305 | 21.90% |
| North America | 4,447 | 42.26% |
| Oceania | 628 | 5.97% |
| South America | 298 | 2.83% |
| **Total** | 10,522 | 100% |

This table reports further sample characteristics. The sample includes 10,522 distinct firms from 2002 to 2022. Panel A shows the number of companies (N) and their fraction of the total sample (Freq.) for each industry sector and Panel B for each continent.

## 8.4 Methodology

To provide a clearer picture of how the relationship between returns and scandals may look like, we employ a panel vector autoregression (PVAR) in the sense of Holtz-Eakin et al. (1988) and Love and Zicchino (2006), which we consider an appropriate econometric technique to derive insights about the dynamic relation between our variables of interest and to disentangle the forward and reverse impact of excess returns and corporate scandals. Simultaneously, we acknowledge that we rely on real-world data for an exhaustive panel data set for which an experimental research design seems inappropriate, especially when we focus on the relation of complex phenomena such as corporate scandals and risk premia.[7]

[7] Nevertheless, following Kang et al. (2016), we take several steps to validate our econometric setup. First, we run an Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and a unit root test to ensure stationarity in our data set. Next, we account for the panel nature of our data and add firm-

Table 8.3: Correlation matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) Number of Scandals | 1 | | | | | | | | |
| (2) Alpha | -0.01 | 1 | | | | | | | |
| (3) ESG Score | 0.20 | -0.05 | 1 | | | | | | |
| (4) Analyst Coverage | 0.23 | -0.07 | 0.35 | 1 | | | | | |
| (5) Size | 0.22 | -0.12 | 0.43 | 0.45 | 1 | | | | |
| (6) Cash | 0.00 | 0.14 | -0.13 | 0.01 | -0.32 | 1 | | | |
| (7) Leverage | 0.00 | -0.04 | 0.08 | -0.05 | 0.27 | -0.36 | 1 | | |
| (8) Book-to-Market | -0.02 | 0.02 | 0.00 | -0.16 | 0.22 | -0.24 | 0.12 | 1 | |
| (9) EPS Surprises | 0.01 | -0.01 | -0.01 | 0.01 | -0.01 | 0.02 | -0.04 | -0.1 | 1 |

This table reports the correlation matrix for the full sample. The sample includes 10,522 distinct firms from 2002 to 2022.

Our PVAR model is estimated with a two-step system Generalized Method of Moments (GMM) process. In the first step, instruments are used to determine the dependent variables and derive preliminary results, which are then used in the second step to derive consistent and efficient estimators for the dynamic relationship.

Concretely, the PVAR model allows a $m \times 1$ vector of endogenous dependent variables ($y_{it}$) to be a function of its lagged set of values ($\sum_{l=1}^{p} \beta_l y_{i(t-l)}$), with $m$ as the number of endogenous variables and $p$ as the length of year lags. Thus, this method allows for a dynamic setup to explore forward and reverse impact simultaneously, which finds common application in the literature (see e.g., Shackleton et al., 2021; Kang et al., 2016; Huang et al., 2008; Grinstein and Michaely, 2005). We define the dynamic relation between the *Number of Scandals (NoS)* and *Alpha* (A) by the following PVAR specification:

$$\begin{bmatrix} NoS_{it} \\ A_{it} \end{bmatrix} = \sum_{l=1}^{p} \begin{bmatrix} \beta_{11}^p & \beta_{12}^p \\ \beta_{21}^p & \beta_{22}^p \end{bmatrix} \begin{bmatrix} NoS_{i(t-p)} \\ A_{i(t-p)} \end{bmatrix} + \begin{bmatrix} \delta^{NoS} C_{i(t-1)} + F_i^{NoS} + Y_t^{NoS} \\ \delta^A C_{i(t-1)} + F_i^A + Y_t^A \end{bmatrix} + \begin{bmatrix} \epsilon_{it}^{NoS} \\ \epsilon_{it}^A \end{bmatrix} \tag{8.1}$$

The vector of endogenous variables $y_{it} = [NoS_{it}, A_{it}]$ contains the *Number of Scandals* and the *Alpha* from the Fama and French (2015) five-factor model for firm $i$ in time $t$, respectively. $p$ represents the lag-length for the endogenous variables (in our case, we employ a lag-length of one year with $p = 1$).[8] $C_{i(t-1)}$ denotes the ($K \times 1$) vector of one-year lagged control variables, where $K$ is the number of control variables and $\delta = [\delta^{NoS}, \delta^A]$

and time-fixed effects. Finally, to increase the precision of our estimates, we follow the suggestions of Blundell and Bond (1998) and use lagged values and changes in the lagged values for endogenous variables as instruments to derive insights about the forward or reverse relationship. Hence, the endogenous variables become pre-determined and are uncorrelated with the error terms (Arellano and Bond, 1991; Arellano and Bover, 1995).

[8] We optimize the lag-length according to the model and moment selection criteria (MMSC) proposed by Andrews and Lu (2001). Specifically, they recommend the MMSC-BIC and MMSC-HQIC, which, in our case, supports a one-year lag.

is the $(1 \times K)$ vector of coefficients corresponding to the control variables.[9] $F_i$ and $Y_t$ represent unobserved firm- and time-fixed effects, and $\epsilon_{it}$ depicts the error term. Note that within the coefficient matrix from equation (8.1)

$$\begin{bmatrix} \beta_{11}^p & \beta_{12}^p \\ \beta_{21}^p & \beta_{22}^p \end{bmatrix}$$

we derive insights about the forward and reverse impact between excess returns and scandals. Statistical significant values of $\beta_{21}^p$ would indicate a forward impact (past scandals affect excess returns), whereas a significant $\beta_{12}^p$ would argue in favor of a reverse impact (past excess returns affect scandals). If the effect would be only correlative, both parameters $\beta_{21}^p$ and $\beta_{12}^p$ would be statistically significant.

To account for firm-fixed effects in equation (8.1) and thus to get rid of unobserved heterogeneity, we apply the forward orthogonal deviation (Arellano and Bover, 1995; Roodman, 2009), which basically subtracts the average of available future values.[10] When compared to a first-difference approach, it minimizes data loss due to potential gaps in our unbalanced panel and is thereby less restrictive in terms of data availability.

Finally, the PVAR model is estimated with a two-step system GMM estimator. In the first step, we use lagged levels and the first-differences of regressors as instruments for our endogenous variables and to estimate the preliminary consistent estimators. In the second step, we use the variance-covariance matrix of residuals from the first step to derive the two-step consistent and efficient GMM estimators.[11]

For estimating the coefficients, we assume the following initial and standard moment conditions:

$$E(y_{i1}\epsilon_{it}) = 0 \text{ (for } i = 1, 2, .., N \text{ and } t = 2, 3, .., T)$$
$$E(y_{i(t-s)}\epsilon_{it}^*) = 0 \text{ (for } i = 1, 2, .., N;\ s \geq 1 \text{ and } t = 2, 3, .., T-1)$$

where $\epsilon_{it}^*$ is the error term after the transformation with the forward orthogonal deviation. This assumes that the lagged endogenous variables are uncorrelated with the error terms

[9] To ensure that the control variables are uncorrelated with the error term, we lag all controls by one year. Thus, we employ the set of one-year lagged control variables, which we described in section 8.3.3, i.e. ESG Score$_{t-1}$, Analyst Coverage$_{t-1}$, Size$_{t-1}$, Cash$_{t-1}$, Leverage$_{t-1}$, Book-to-Market$_{t-1}$ and EPS Surprise$_{t-1}$.

[10] Let $z_{it+1}^{\perp}$ be the value of a variable $w_{it}$ that was transformed with the forward orthogonal deviation, then $z_{it+1}^{\perp} \equiv c_{it}(w_{it} - \frac{1}{T_{it}} \sum_{s>t}^{T_{it}} w_{is})$, with $c_{it} = \sqrt{\frac{T_{it}}{(T_{it}+1)}}$ as a scale factor and $T_{it}$ as the number of future observations (Arellano and Bover, 1995; Roodman, 2009; Sigmund and Ferstl, 2021). When applied to our PVAR model, the firm-fixed effects $(F_i)$ are time-invariant and thus are accounted for within this transformation.

[11] With regards to the complex distribution of the *Number of Scandals* variable, the GMM estimator is considered an appropriate technique, as it does not require detailed a priori assumptions about the distribution of our data. We can further relax the distributional assumptions through the transformation with the forward orthogonal deviation.

(orthogonality property). Furthermore, we follow the suggestions of Blundell and Bond (1998) and add first-differences of the endogenous variables as additional instruments (i.e. performing a *system GMM* estimation). This implies the following additional $T-2$ moment conditions:

$$E[\Delta y_{i(t-1)}(\epsilon_{it} + F_i)] = 0 \text{ (for } i = 1,2,..,N \text{ and } t = 3,4,..,T)$$

where $\Delta$ expresses the first-difference transformation.

This leaves us with a minimum of $T \geq m+1 = 3$ observations to estimate the PVAR model.[12] The instrument matrix $Q_i^* = \begin{bmatrix} Q_i & 0 \\ 0 & P_i \end{bmatrix}$ summarizes our employed instruments,[13]

$$\text{with } Q_i = \begin{bmatrix} q'_{i(p+1)} & 0 & 0 & ... & 0 \\ 0 & q'_{i(p+2)} & 0 & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & ... & q'_{i(T-1)} \end{bmatrix}; P_i = \begin{bmatrix} 0 & \Delta y_{i2} & 0 & ... & 0 \\ 0 & 0 & \Delta y_{i3} & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & ... & \Delta y_{i(T-1)} \end{bmatrix}$$

and $q'_{it} = [y_{i(t-p-1)}, y_{i(t-p-2)}, ..., y_{i1}, \Delta C'_{i(t-1)}]$.

## 8.5 Results

This section exhibits the central statistical results of the PVAR model and derives the generalized impulse response functions to further verify our results. Next, we employ propensity score matching to address a potential selection bias in our sample and an analysis of economic channels that moderate the dynamic relation between *Alpha* and *Number of Scandals*. A discussion on the economic significance closes the results section.

### 8.5.1 Baseline Results

Table 8.4 displays the results derived from the second step of our PVAR model with firm- and time-fixed effects. Consistent with our prior arguments, we find a statistical significant positive effect of the one-year lagged $Alpha_{it-1}$ on the current *Number of Scandals* $NoS_{it}$ ($\beta_{12} = 0.0118^{***}$), which suggests that firms with higher excess returns will undergo more scandals in the future.

In contrast, the coefficient of lagged *Number of Scandals* $NoS_{it-1}$ on the current $Alpha_{it}$

[12] For a more in-depth explanation of the system GMM estimation process and the moment conditions, see e.g., Sigmund and Ferstl (2021) and Roodman (2009).

[13] For computational reasons, we limit the number of employed lagged instruments to 10. This seems reasonable, as we do not assume any influence of instruments with a longer year lag. However, our baseline results remain the unchanged if we employ the full set of available instruments.

Table 8.4: PVAR estimation of the dynamic relation between *Alpha* and *Number of Scandals*

| *Alpha* and *Number of Scandals* | | |
|---|---|---|
| | $NoS_{it}$ (1) | $Alpha_{it}$ (2) |
| $Alpha_{it-1}$ | **0.0118**$^{***}$ | $-0.0047$ |
| | (0.0030) | (0.0080) |
| $NoS_{it-1}$ | 0.4196$^{***}$ | $\mathbf{-0.0010}$ |
| | (0.0912) | (0.0030) |
| $ESG\ Score_{it-1}$ | **0.0045**$^{***}$ | $-0.0000$ |
| | (0.0010) | (0.0003) |
| $\text{Controls}_{t-1}$ | Yes | Yes |
| Firm-fixed effects | Yes | Yes |
| Year-fixed effects | Yes | Yes |
| Observations | 39,811 | 39,811 |

This table presents the results of the second step of the panel vector autoregression. The PVAR is estimated with a two-step system GMM approach. The dependent variables are the *Number of Scandals* ($NoS_{it}$) and the firm's excess return ($Alpha_{it}$). We use the one-year lagged control variables discussed in section 8.3.3 ($ESG_{it-1}$, $Size_{it-1}$, $AC_{it-1}$, $Cash_{it-1}$, $Lev_{it-1}$, $Book\text{-}to\text{-}Market_{it-1}$ and $EPS\ Surprises_{it-1}$). To account for firm-fixed effects, we use the forward orthogonal deviation (Arellano and Bover, 1995). z-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

($\beta_{21} = -0.0010$) is insignificant, which suggests that past scandals that were exposed to the public have no significant positive or negative impact on future excess returns. As mentioned in Section 8.4, correlation would be indicated by statistical significance in both directions across time. Overall, these findings support our claim of reverse impact (past excess returns affect scandals) instead of a forward relationship. Furthermore, we find a statistical significant positive effect of the *Number of Scandals* $NoS_{it-1}$ on their future values $NoS_{it}$ ($\beta_{11} = 0.4196^{***}$), indicating that a company's general tendency towards (un-)ethical behavior remains consistent over time. Finally, for the *ESG Score*, we observe only a statistical significant effect with scandals in the future. As proposed by literature, we find evidence in favor of the insurance mechanism, i.e. the negative relation between CSR and corporate scandals (see e.g., Godfrey, 2005). Furthermore, this is in favor of the *No effect by doing good* hypothesis (see e.g., Shackleton et al., 2021), although we do not claim causal relations here.

To ensure that our results are not affected by extreme values of *Alpha*, as already mentioned in Section 8.3.4, we run the PVAR again with several adjustments to the variable. The results are displayed in Table 8.5. First, in Panel A, we utilize $Alpha^{Win}$ winsorized at stricter levels of 10% and 90%. For $Alpha^{IR}$ in Panel B, we remove observations of *Alpha* that exceed two times the interquartile range. Additionally, in panel C, we vary the method used to derive *Alpha* and calculate $Alpha^{MM}$ as the annualized intercept of the market model based on a non-overlapping twelve-month return window.

Compared with our baseline results, the effect of past excess returns on future scandals

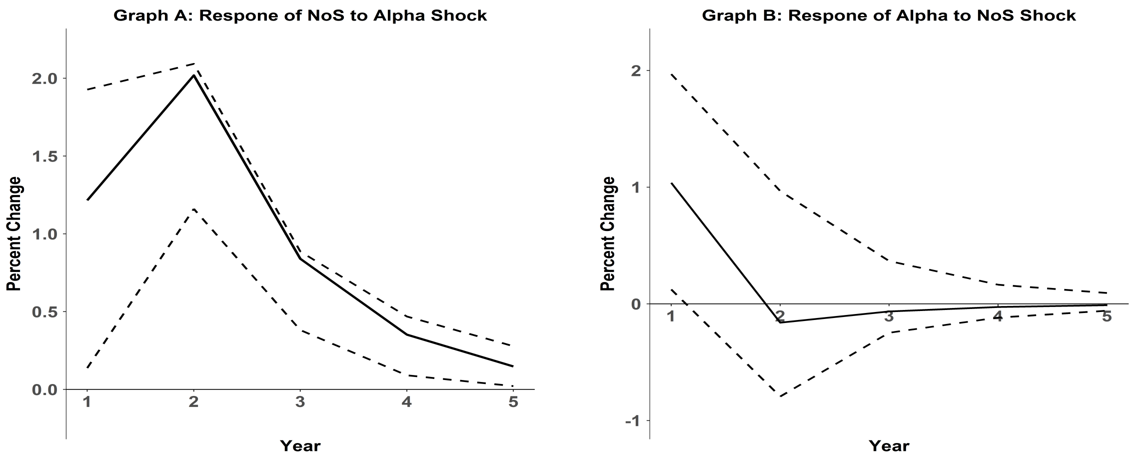
($\beta_{12}$) is more present in terms of magnitude in all three panels. The coefficients of $\beta_{12}$ remain statistical significant, despite the loss of around 5,000 observations in panel B.

### 8.5.2 Generalized Impulse Response Function

Next, we determine the generalized impulse response functions (GIRF; Pesaran and Shin, 1998) with bootstrapped confidence intervals based on the results of the PVAR model in the previous section.[14] Generally, this approach describes how a one-unit shock (impulse) of one endogenous variable affects the other endogenous variable in the system over time (response). It thus allows us to derive further insights into the dynamic interplay of returns and scandals over time.

Figure 8.2 presents the GIRF for our two variables of interest (solid lines) with the bootstrapped 95% upper and lower confidence bands (dashed lines). Graph A displays the response of *Number of Scandals* to a shock in *Alpha* over a period of 5 years. In line with our claim of reverse impact, a 1% increase in *Alpha* is associated with a statistical significant increase in the *Number of Scandals* by $1,28\%$ in the first year. This effect increases to almost 2% for the second year and then slowly decreases over time. Graph B presents the response of *Alpha* to a shock in the *Number of Scandals* and we find a positive effect in the first year. However, the effect becomes insignificant within one year (i.e. the confidence brand includes the zero shortly after the first year) and eventually turns negative in the second year. Thus we do not find supporting evidence in favor of a forward impact based on the GIRF.

Figure 8.2: Generalized impulse response function.




This figure illustrates the generalized impulse response function (solid line) and the bootstrapped 95% upper and lower confidence bands (dotted lines) for our endogenous variables. The left graph shows the response of *Number of Scandals (NoS)* to a shock of *Alpha*, and vice-versa is displayed on the right.

[14] One important gain in using a GIRF over the orthogonal impulse response function is the fact that the GIRF is not affected by the ordering of the variables (Sigmund and Ferstl, 2021).

Table 8.5: Additional PVAR estimations of the dynamic relation between *Alpha* and *Number of Scandals*

| **Panel A.** $Alpha^{Win}$ and *Number of Scandals* | | |
|---|---|---|
| | $NoS_{it}$<br>(1) | $Alpha_{it}^{Win}$<br>(2) |
| $Alpha_{it-1}^{Win}$ | **0.0427**$^{***}$ | $-0.0258^{***}$ |
| | (0.0107) | (0.0062) |
| $NoS_{it-1}$ | $0.4256^{***}$ | **−0.0004** |
| | (0.0850) | (0.0021) |
| $ESG\ Score_{it-1}$ | **0.0042**$^{***}$ | −0.0002 |
| | (0.0009) | (0.0002) |
| Controls$_{t-1}$ | Yes | Yes |
| Firm-fixed effects | Yes | Yes |
| Year-fixed effects | Yes | Yes |
| Observations | 39,811 | 39,811 |

| **Panel B.** $Alpha^{IR}$ and *Number of Scandals* | | |
|---|---|---|
| | $NoS_{it}$<br>(1) | $Alpha_{it}^{IR}$<br>(2) |
| $Alpha_{it-1}^{IR}$ | **0.0332**$^{**}$ | −0.0091 |
| | (0.0137) | (0.0064) |
| $NoS_{it-1}$ | $0.4003^{***}$ | **−0.0007** |
| | (0.0702) | (0.0015) |
| $ESG\ Score_{it-1}$ | **0.0047**$^{***}$ | 0.0001 |
| | (0.0008) | (0.0001) |
| Controls$_{t-1}$ | Yes | Yes |
| Firm-fixed effects | Yes | Yes |
| Year-fixed effects | Yes | Yes |
| Observations | 34,324 | 34,324 |

| **Panel C.** $Alpha^{MM}$ and *Number of Scandals* | | |
|---|---|---|
| | $NoS_{it}$<br>(1) | $Alpha_{it}^{MM}$<br>(2) |
| $Alpha_{it-1}^{MM}$ | **0.0281**$^{***}$ | −0.0043 |
| | (0.0079) | (0.0085) |
| $NoS_{it-1}$ | $0.3850^{***}$ | **−0.0002** |
| | (0.0850) | (0.0014) |
| $ESG\ Score_{it-1}$ | **0.0049**$^{***}$ | −0.0001 |
| | (0.0009) | (0.0001) |
| Controls$_{t-1}$ | Yes | Yes |
| Firm-fixed effects | Yes | Yes |
| Year-fixed effects | Yes | Yes |
| Observations | 39,811 | 39,811 |

This table presents the results of the second step of the panel vector autoregression. The PVAR is estimated with a two-step system GMM approach. In Panel A, the firm's excess return $Alpha_{it}^{Win}$ is winsorized at 10% and 90% levels. For $Alpha_{it}^{IR}$ in panel B, we exclude all *Alpha* that exceed the double interquartile range. Panel C derives $Alpha_{it}^{MM}$ as the annualized intercept based on the market model. We use the one-year lagged control variables discussed in section 8.3.3 ($ESG_{it-1}$, $Size_{it-1}$, $AC_{it-1}$, $Cash_{it-1}$, $Lev_{it-1}$, $Book\text{-}to\text{-}Market_{it-1}$ and $EPS\ Surprises_{it-1}$). To account for firm-fixed effects, we use the forward orthogonal deviation (Arellano and Bover, 1995). z-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

### 8.5.3 Disclosure of Scandals

Although our results support reverse instead of forward impact, we still need to address some concerns arising from our previous results that could distort our findings. One is a potential selection bias, because some unobserved factors may influence the (non-)disclosure of scandals and hence impact the dynamic interplay of our endogenous variables. Thus, we use propensity score matching (PSM) to create more balanced samples, which is a common technique to account for a potential selection bias.

For that, we define two dummy variables: (1) $D_{Alpha}$, which equals one if *Alpha* of a firm exceeds the mean in our sample for a given year and 0 otherwise, and (2) $D_{NoS}$, which equals one if a firm has at least one scandal in a given year and 0 otherwise. Then, we calculate the probability (i.e. the propensity score) for each observation to be in the treatment group ($D_{Alpha}$ or $D_{NoS}$ equal to 1) based on a set of covariates $X = (x_1, ..., x_k)$ for each of the two dummy variables separately. Since the potential effect is to be found in returns, it seems reasonable to use the beta coefficients derived from the Fama and French (2015) five-factor regression for the matching based on $D_{Alpha}$ and to employ our firm controls together with the industry classification for the matching based on $D_{NoS}$.

For the matching approach, we follow recent literature (see e.g., Roberts and Whited, 2013; Dehejia and Wahba, 2002) and employ nearest neighbor matching (with replacement) and a logistic link to match treated and untreated observations within the same year. Finally, to determine the effect of *Alpha* on the *Number of Scandals* and vice versa, we run an OLS regression with fixed effects and firm-level clustered standard errors for both matched samples.[15]

Table 8.6 reports the results of the OLS regression for both matching approaches. Column (1) shows the regression estimations for the matched sample based on $D_{Alpha}$, and column (2) for the sample matched by $D_{NoS}$.[16] The coefficient of the dummy $D_{Alpha,t-1}$ is statistical significant and positive, whereas the coefficient on $D_{NoS,t-1}$ is insignificant. This shows that firms with an outperformance (i.e. treatment dummy $D_{Alpha} = 1$) will undergo more scandals in the future, but having a scandal (i.e treatment dummy $D_{NoS} = 1$) will not impact future excess returns. Ultimately, this again supports our claim that past excess returns affect future scandals.

[15] For industry classification, we use the Refinitiv Business Classification. Our results remain largely unchanged if we use Standard Industry Classification (SIC) codes for grouping. Furthermore, in unreported results, we include the beta coefficients (which we use to calculate the propensity score in the first place) in the OLS regression to increase the robustness of the results displayed in column (1). The results remain unchanged.

[16] The reduction in sample size in column (2) is due to the fact that the treatment variable $D_{NoS} = 1$ requires a firm to have a positive count of scandals, which is a relatively rare event (see section 8.3.4).

Table 8.6: OLS regression with fixed effects based on the matched sample

| | NoS (1) | Alpha (2) |
|---|---|---|
| Constant | $-3.7412^{***}$ | $2.6806^{***}$ |
| | $(-6.4877)$ | $(3.7210)$ |
| $D_{Alpha,t-1}$ | $\mathbf{0.0627}^{***}$ | |
| | $(2.7567)$ | |
| $D_{NoS,t-1}$ | | **0.0035** |
| | | $(0.1511)$ |
| ESG Score$_{t-1}$ | $0.0051^{**}$ | $-0.00003$ |
| | $(2.3106)$ | $(-0.0261)$ |
| Analyst Coverage$_{t-1}$ | $0.0017$ | $-0.0017$ |
| | $(0.2648)$ | $(-0.7422)$ |
| Size$_{t-1}$ | $0.1400^{***}$ | $-0.1313^{***}$ |
| | $(3.1053)$ | $(-2.8040)$ |
| Cash$_{t-1}$ | $-0.2300$ | $0.0732$ |
| | $(-0.9289)$ | $(0.3790)$ |
| Leverage$_{t-1}$ | $-0.0173$ | $0.0861$ |
| | $(-0.0874)$ | $(0.5104)$ |
| Book-to-Market$_{t-1}$ | $-0.0158$ | $0.1142^{***}$ |
| | $(-0.3987)$ | $(3.2834)$ |
| EPS Surprise$_{t-1}$ | $-0.0033$ | $-0.0012$ |
| | $(-0.6353)$ | $(-0.1777)$ |
| Year-fixed effects | Yes | Yes |
| Firm-fixed effects | Yes | Yes |
| Industry-fixed effects | Yes | Yes |
| Country-fixed effects | Yes | Yes |
| Observations | 27,598 | 10,834 |
| Adjusted $R^2$ | 0.3959 | 0.1537 |
| VIF (min) | 1.0180 | 1.0783 |
| VIF (max) | 3.4432 | 4.2962 |

This table reports the results from the OLS regression with year-, firm-, industry- and country-fixed effects based on the propensity score sampling approach with nearest neighbor matching. Column (1) shows the results for the sample when the matching is based on the $D_{Alpha}$ variable, and column (2) for the sample matched by $D_{NoS}$. t-statistics are reported in parentheses and $*$, $**$, $***$ indicate a 10%, 5%, and 1% level of significance, respectively. Adjusted $R^2$ and the minimum and maximum variance inflation coefficients (VIF) are reported upon.

### 8.5.4 About the Moderating Effect of Size and CSR reputation

In this section, we expand the PVAR model presented in Section 8.4 to derive insights about potential moderating channels that affect the empirical link between *Alpha* and *Number of Scandals*.

First, drawing upon the definition of a scandal of Dorfleitner et al. (2022), we acknowledge that we require both components for a scandal to occur: unethical corporate behavior and its disclosure. Generally, the actual unethical behavior and, consequently, the dynamic relation between *Alpha* and *Number of Scandals* depends primarily on the company's orientation towards sustainable and ethical norms and values. On the one hand, companies may more likely engage in unethical behavior to enhance short-term profit and achieve the demanded returns if they are not concerned about their impact on the environment or if they do not emphasize implementing an ethical corporate governance policy. In contrast, some studies highlight the insurance-like mechanism of CSR (see e.g., Godfrey, 2005; Bhattacharya and Sen, 2004; Peloza, 2006; Gardberg and Fombrun, 2006), which protects the firm from severe consequences following a scandal. Without this disciplining mechanism, companies with high ESG ratings may be tempted to abandon ethical behavior in favor of competition-enhancing unethical practices.

Second, we acknowledge that large and small companies differ in various ways regarding their visibility, the availability of company-related information, and their ability to achieve demanded returns. Larger companies tend to be more newsworthy and are subject to intensified public scrutiny (Watts and Zimmerman, 1986; Reverte, 2009; Servaes and Tamayo, 2013) but can simultaneously use their tremendous financial resources to cover up their own unethical behavior and to hamper the disclosure of scandals. On the other hand, smaller firms are less present in the media spotlight and lack the financial resources to disguise potential unethical behavior.

We use three measures to split our sample and then estimate the PVAR model described in Section 8.4 for each subsample again, allowing us to address these potential moderating channels separately. For the *Size* channel, we split our sample in large and small firms according to the median of the *Size* variable each year.[17] Regarding the *Environmental* and *Governance* channel, we use the median of the *Environmental Score* and the *Corporate Governance Score* each year to split our sample. These scores measure a company's efforts to reduce environmental pollution, greenhouse gas emission, and resource waste, as well as the company's willingness to establish a stable CSR policy and protect shareholder rights.[18]

Table 8.7 reports the results of the second step of our PVAR model with firm- and time-fixed effects for each subsample. Columns (1) to (4) present the results for the *Size* channel. Regarding the beta coefficients for $Alpha_{t-1}$ in columns (1) and (3), we find supportive evidence for our claim that the dynamic relation between *Alpha* and *Number of Scandals* differs between large and small companies. While we find a statistical significant positive coefficient for large companies in column (1), the coefficient for small firms in column (3)

[17] In unreported results, we also used *Analyst Coverage* as a proxy for firm size and visibility. The results remain largely unchanged.

[18] A detailed description of these variables can be found in Table A.1 in the appendix.

is insignificant. Thus, firm size and visibility moderate the dynamic relation as large firms, in particular, show that high returns are associated with more scandals in the future.

Columns (5) to (8) and (9) to (12) of Table 8.7 present the results for the sample split according to a firm's environmental or corporate governance efforts, respectively. Consistent with the literature on the insurance-like mechanisms of CSR, we find positive and statistical significant coefficients of $Alpha_{t-1}$ for our subsamples with a high *Environmental Score* (column 5) and high *Governance Score* (column 9). In contrast, we find no statistical significant effect in the low subsamples (column 7 with a low *Environmental Score* and column 11 with a low *Governance Score* ). Firms with high environmental or corporate governance scores rely on their current good reputation and may neglect ethical behavior to achieve the required financial performance.

Table 8.7: PVAR estimation of the relation between the *Number of Scandals* and *Alpha* for the economic channels

| | Size | | | | Environmental Score | | | | Governance Score | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High | | Low | | High | | Low | | High | | Low | |
| | $NoS_{it}$ | $Alpha_{it}$ | $NoS_{it}$ | $Alpha_{it}$ | $NoS_{it}$ | $Alpha_{it}$ | $NoS_{it}$ | $Alpha_{it}$ | $NoS_{it}$ | $Alpha_{it}$ | $NoS_{it}$ | $Alpha_{it}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $Alpha_{it-1}$ | **0.0425**$^{**}$ | −0.0243$^{*}$ | **−0.0013** | −0.0071 | **0.0450**$^{**}$ | −0.0255$^{*}$ | **0.0017** | −0.0002 | **0.0303**$^{*}$ | −0.0083 | **0.0017** | −0.0386 |
| | (0.0136) | (0.0096) | (0.0011) | (0.0096) | (0.0145) | (0.0117) | (0.0018) | (0.0101) | (0.0143) | (0.0159) | (0.0026) | (0.0281) |
| $NoS_{it-1}$ | 0.4294$^{***}$ | **−0.0013** | 0.1767$^{***}$ | **−0.0436** | 0.4484$^{***}$ | **−0.0021** | 0.2925$^{***}$ | **0.0149** | 0.3588$^{***}$ | **−0.0063** | 0.2382$^{***}$ | **−0.0046** |
| | (0.0969) | (0.0029) | (0.0927) | (0.0782) | (0.1151) | (0.0037) | (0.0338) | (0.0184) | (0.0680) | (0.0052) | (0.0564) | (0.0170) |
| Controls$_{t-1}$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 28,734 | 28,734 | 9,074 | 9,074 | 20,360 | 20,360 | 12,848 | 12,848 | 15,116 | 15,116 | 11,959 | 11,959 |

This table presents the results of the second step of the panel vector autoregression. For the dependent variables $NoS_{it}$ and $Alpha_{it}$, we estimate the PVAR model with a two-step system GMM estimator. In Columns (1) to (4), we use the median of *Size* of each year to divide the sample into firms with high and low shareholder attention and visibility. Columns (5) to (8) display the results when the sample is divided into high and low according to the median of the *Environmental Score* each year and Columns (9) to (12) when the sample is divided according to the median of the *Governance Score*. We use the same set of one-year lagged control variables ($ESG_{it-1}$, $Size_{it-1}$, $AC_{it-1}$, $Cash_{it-1}$, $Lev_{it-1}$, $Book\text{-}to\text{-}Market_{it-1}$ and $EPS\ Surprises_{it-1}$) as in section 8.5.1. To account for firm-fixed effects, we use the forward orthogonal deviation (Arellano and Bover, 1995). The different sample sizes result from missing control variables and data losses due to the forward orthogonal deviation in the PVAR model. z-statistics are displayed in parentheses and $*$, $**$, and $***$ indicate a 5%, 1%, and 0.1% level of significance, respectively.

### 8.5.5 Economic Significance

To derive practical implications for managers, shareholders, and the broader society, we need to assess the magnitude of the relation between *Alpha* and *Number of Scandals*. Although we find supportive evidence for our theoretical reasoning through the PVAR model and the propensity score matching approach in the previous sections, we prefer to use statistical models that are more easy to interpret to assess the economic significance of our results. For that, we use the two most common methods, a simple Tobit Regression (Tobin, 1958) (because the $NoS$ variable is left-censored at zero) as well as a Negative Binomial model (because the $NoS$ is a count variable).

Column (1) of table 8.8 illustrates the results for the Tobit model with firm-level clustered standard errors. In terms of economic interpretation, a one-unit increase in *Alpha* equals 0.065 discovered scandals per year or a 30.95 percent increase above the mean of the full sample. Similarly, the positive statistically significant beta coefficient in the Negative Binomial Model in column (2) indicates for every unit increase in *Alpha* an increase of 0.037 in the expected log of *Number of Scandals*.

As public awareness and efforts to expose unethical behavior by rating agencies, NGOs, journalists, and investors have increased tremendously, there is an upward trend in discovering corporate scandals. Figure 8.3 highlights this trend and shows the *Number of Scandals* divided by the number of firms per industry sector over time. Assuming that companies now are not more ethical than in the past and, therefore, many scandals have been covered up in the past 18 years, the effect of outperformance and scandals is likely to be drastically underestimated. If a company's unethical behavior remains hidden, there is no measurable response to a scandal. Therefore, we recognize the potential problem of excess (false) zeros in our sample when scandals are not detected. We address this issue by using a Zero-Inflation Negative Binomial Model (ZINB) and a Hurdle Model.

The results are displayed in Table 8.8 columns (3) and (4). Consistent with our earlier results, we find a positive and statistical significant link between prior *Alpha* and future *Number of Scandals* in both models. The positive count component of the Hurdle model in column (4) indicates that, all else being equal, a one-unit increase in *Alpha* increases the *Number of Scandals* among those who have positive counts by about 0.14 per year.

## 8.6 Conclusion

This paper unravels the relationship between past excess returns and future scandals. It challenges the traditional notion that scandals are unpredictable and are incorporated in prices and returns only after they occur, as well as the usual temporal perspective of current ethical and sustainable behavior and future financial performance. Furthermore,

Table 8.8: Statistical analysis of the economic significance

| | Number of Scandals | | | |
|---|---|---|---|---|
| | *Tobit* | *Negative Binomial* | *ZINB* | *Hurdle* |
| | (1) | (2) | (3) | (4) |
| $\text{Alpha}_{t-1}$ | 0.0650*** | 0.0370*** | 0.1115*** | 0.1359*** |
| | (2.9790) | (5.4549) | (6.5929) | (4.9031) |
| $\text{ESG Score}_{t-1}$ | 0.0551*** | 0.0179*** | 0.0144*** | 0.0138*** |
| | (9.7623) | (22.9874) | (16.3254) | (12.0230) |
| $\text{Analyst Coverage}_{t-1}$ | 0.0787*** | 0.0202*** | 0.0127*** | 0.0116*** |
| | (4.1033) | (10.3664) | (6.6738) | (4.2832) |
| $\text{Size}_{t-1}$ | 2.3066*** | 0.8307*** | 0.7841*** | 0.6631*** |
| | (10.2647) | (52.7100) | (44.9614) | (26.9298) |
| $\text{Cash}_{t-1}$ | 3.3965*** | 1.2433*** | 1.7742*** | 1.7466*** |
| | (4.1334) | (11.2228) | (11.5738) | (8.5571) |
| $\text{Leverage}_{t-1}$ | −0.7493 | −0.1508* | −0.4407*** | −0.1073 |
| | (−1.6184) | (−1.7621) | (−4.0964) | (−0.7096) |
| $\text{Book-to-Market}_{t-1}$ | 0.0406 | 0.0125 | −0.1028*** | −0.1006*** |
| | (0.4373) | (0.6437) | (−4.7831) | (−3.2521) |
| $\text{EPS Surprises}_{t-1}$ | −0.0714*** | −0.0314*** | −0.0086 | −0.0156 |
| | (−2.6968) | (−4.5553) | (−0.9806) | (−1.2861) |
| Year-fixed effects | Yes | Yes | Yes | Yes |
| Industry-fixed effects | Yes | Yes | Yes | Yes |
| Country-fixed Effects | Yes | Yes | No | No |
| Observations | 46,653 | 46,653 | 46,653 | 46,653 |
| Firm-clustered SE | Yes | / | / | / |
| Log Likelihood | −34,507.89 | −29,647.89 | −30,279.17 | −30,037.07 |
| AIC | 69.175,78 | 59,453.78 | 59,375.27 | 58,857.52 |
| BIC | 69.875,82 | 60.153,82 | 60,241.57 | 59,723.82 |

This table reports the Tobit, the Negative Binomial, the Zero-Inflated Negative Binomial (ZINB), and Hurdle Model with year- and industry-fixed effects for the relation between the *Number of Scandals* and Fama and French (2015) five-factor *Alpha* for all companies. The *Number of Scandals* is the actual sum of all scandals a firm is involved in a fiscal year. Due to the possibility that a firm's unethical behavior may remain hidden, the actual sum of scandals may show excess (false) zeros. The ZINB and the Hurdle model account for this, with further diagnostic statistics omitted for presentation reasons. Column (3) presents the count coefficient for the ZINB model, and column (4) reports the coefficient of positive counts for the Hurdle model. The Log-Likelihood as well as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are reported upon. z-statistics are reported in parentheses and $*$, $**$, $***$ indicate a 10%, 5%, and 1% level of significance, respectively.

the results justify a separation between being good in terms of sustainability and being good or ethically correct in terms of not undergoing public scandals. Since firms cannot alter the societal perception of disclosed scandals so easily, the number of scandals used in this context is less susceptible to interpretation and measurement biases than CSR, and evades the black-box nature of ESG ratings.

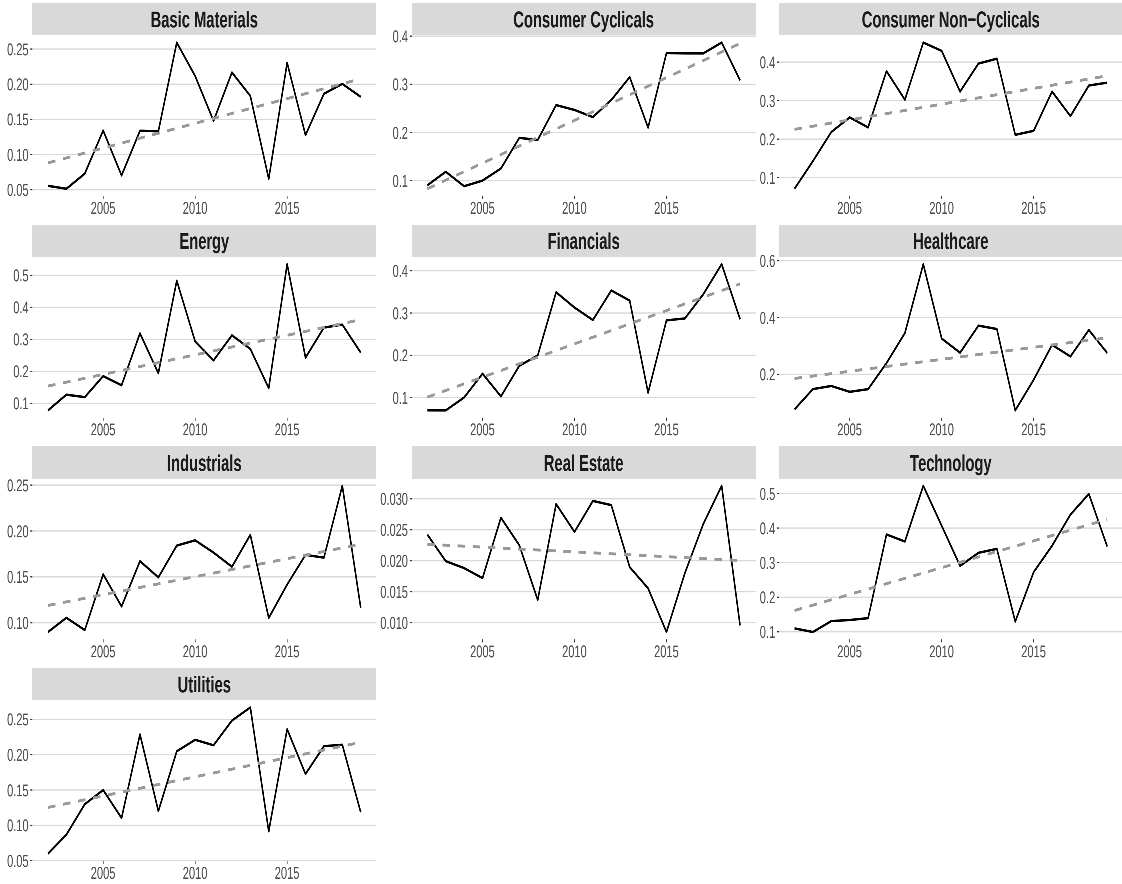



Figure 8.3: Corporate scandals across industry sectors.

This figure illustrates the *Number of Scandals* divided by the number of firms for each year and each industry sector (solid line) for 2002-2022 to account for the growing number of companies being monitored. The dashed line represents the trend line.

This study shows from various angles and statistical methods that there is a counterintuitive relationship between excess returns, sustainability, and ethical behavior. Outperfomance within financial markets, measured in excess returns, can be used as a statistical predictor for future uncovered unethical behavior. Thereby all models show that a high sustainable reputation is an indicator of unethical behavior rather than vice versa. This goes in line with contradicting research in terms of returns and sustainability of companies.

The implications for investors, regulators, as well as academics are essential for their focus of attention: Excess returns and thereby financial outperformance serve as risk compensation also in terms of potential corporate misconduct. Since past outperformance and high ESG ratings are important investment criteria, unaware investors are more likely to engage in corporate misconduct inadvertently. A good rating in terms of sustainability, such as the ESG rating used in this study, should by far not be the only key measure for being good in terms of correct ethical behavior, good governance, sustainability, or greenness. The results of this study also have practical implications for asset management and portfolio management. While we do not claim that every outperformance is related to a scandal, the findings can be used as a screening tool to focus investment analysis on high financial performance as well as on outstanding sustainability in terms of ratings. All participants within financial markets should face the conflicting goals of excess returns, which reflect risk compensation, and acting towards a responsible and sustainable corporate future. Today, the trade-off between profitability and correct behavior may be hidden by more or less favorable rating settings, but ethical behavior will not necessarily maximize shareholders' return in the short run.

Future research needs to focus on the identification of unethical behavior as well as a more precise and frequent measurement. Although this study is somehow flawed by the use of this kind of metric itself, it points to the apparent problems of today's financial markets, high financial performance versus ethically correct behavior, and sustainability. The wishful thinking that exaggerating returns in a broad scale can be achieved in an ethical and sustainable way is not in line with efficient capital markets and risk compensation. Therefore, investors need to prioritize what is important to them: Either excess returns, which may even be accompanied by a short-term greenness of their investments, or long-term responsible and ethical corporate behavior. Since the measurement of sustainability used in this study is inversely related to corporate scandals, something is going terribly wrong. This mismatch is probably even masked by the fact that we most likely cannot ensure that our sample covers all scandals that companies have been involved in.

# Appendix

Table A.1: Description of Variables

| | |
|---|---|
| Number of Scandals | The sum of a company's actual number of scandals in a given year. This variable accounts for 23 concrete CSR-related scandal topics that occur during a company's fiscal year, such as employee diversity, product responsibility and safety, tax fraud, or environmental issues (see Refinitiv, 2022). Refinitiv collects these information from various international sources, including media sources (such as Bloomberg, Reuters News, FT, or LexisNexis), NGOs (such as Amnesty International, Human Rights Watch, or Greenpeace), and the company's own reports. To capture severity and magnitude of a scandal, a large scandal is counted multiple times if it affects different scandal topics and may also be accounted for in the following years if there are ongoing news about the scandal (for example lawsuits). |
| Alpha | The annualized intercept of the Fama and French (2015) five-factor model, based on a non-overlapping twelve-month return window. To ensure the robustness of our baseline results, we additionally use several versions of the variable. $Alpha^{Win}$ is winsorized at a stricter level of 10% and 90%. For $Alpha^{IR}$, we remove all observations that exceed twice the interquartile range. $Alpha^{MM}$ is the annualized intercept of the market model, based on a non-overlapping twelve-month return window. |
| ESG Score | The aggregated ranking of a company's environmental (E), social (S), and corporate governance (G) commitment (on a scale of 0 to 100) relative to its peer group. |
| Analyst Coverage | The number of analysts who provide earnings forecasts for the firm. |
| Size | The natural logarithm of total assets (converted to US dollar). |
| Cash | The ratio of cash and short-term investments to total assets. |
| Leverage | The ratio of (long- and short-term) debt to total assets. |
| Book-to-Market | The natural logarithm of the book-to-market ratio of common stock. |
| EPS Surprises | The difference between the actual (reported) earnings and the Refinitiv Surprise mean estimates, divided by the standard deviation of the Refinitiv Surprise mean estimates. |
| Environmental Score | A ranking of a company's environmental (E) commitment (on a scale of 0 to 100) relative to its peer group. It measures various ecological aspects, such as resource use, greenhouse gas emission, and ecological innovations. |
| Governance Score | A ranking of a company's corporate governance (G) commitment (on a scale of 0 to 100) relative to its peer group. It accounts for CSR policies and reporting, shareholder rights, management compensation and board structure. |

This table presents a detailed explanation of our employed variables. All variables are obtained from Thomson Reuters Datastream.

# Chapter 9

# Conclusion

This final section comprises several aspects regarding insights and issues encountered within the chapters and points to future research opportunities. Section 9.2 closes the dissertation with a general outlook regarding the underlying themes.

## 9.1 Limitations and Remarks

The biggest limitation of this dissertation, as well as for efficient markets, is the aggregation and evaluation of all information available. Within chapter 2, the traceability of the blockchain technology is used for one of the first economic studies of the tokenization of real estate. It is shown, by analyzing individual transactions, that although some crypto-specific factors influence investor behavior, still classical financial and macro-econonomic factors are the foundation for this emerging field. However, the data availability is limited, which is caused naturally by the novelty of the technology. To our best knowledge, there are yet not many businesses following this approach of tokenizing real estate, especially with public blockchains. Since the technology itself is a solution for outlined classical problems of real estate investment, e.g. illiquidity, there is further potential in the usage of blockchain technologies. However, the ongoing success of existing solutions and the identification of new innovations within this realm should be promising for practitioners and researchers alike.

Chapter 3 contributes by shedding light on the German FinTech landscape and also publishing the gathered data open-access. Since many of these companies are start-ups and are mostly not publicly traded, it is difficult to get a holistic and nationwide picture of such an industry. The study therefore supports researchers, regulators, and practitioners to get a comprehensive overview of all companies attributed to the FinTech segment and the related taxonomy following Dorfleitner et al. (2017). Furthermore, it estimates with accordance to the specifics of certain segments the market volume to be around €85.3 billion at the end of 2021. Naturally, caused by the dynamic of these field and technologies, this study offers insights just for a certain time span and for specific domains. The market of FinTechs is more and more mature, they rather seek cooperation with financial intermediaries than trying to disrupt the traditional financial industry. This blurs the lines between FinTechs and the regular financial industry. Future research can now focus on how the Fintech ecosystem is evolving and changing financial markets, as outlined for example by Gargano and Rossi (2024).

The accessibility, transparency, and desirable larger datasets are also one limitation of chapter 4 regarding the STO market. Since both topics are innovative with respect to the technology, and at the time the datasets were created, data was rare. However, sufficient samples for statistical power could be generated and provide first insights in these new markets, where traditional finance theory in form of signaling within offerings is proven once again to be true. It also reveals new crypto specifics, like the local preference for regulatory advanced countries.

Contrary to chapter 2 to 4, the focus in chapter 5 lies on methodological improvement. In the context of digital finance, a novel approach of natural language processing with the help of machine learning is employed to solve the problem of quantifying written language within finance and accounting. It is shown, by the usage of the structural topic model by Roberts et al. (2019) in contrast to the common approach of Blei et al. (2003), that more meaningful and statistical powerful abstractions of text can be generated. Since the quantification of language is a powerful tool for analyzing quarterly and annual reports, news, headlines, articles, and even social media, improvement in the area of gaining quantifiable information out of human language is an ongoing important topic in academia. Furthermore, with the emergence of large language models, there are countless new topics and techniques to extract relevant information in financial markets.

Given the importance and disruptive potential of all these aspects for digital finance, market efficiency, and the transformation of capital markets, future research should focus on new and different data sources to further corroborate the insights presented in this dissertation and to add new perspectives. It is academia's task to guide investors, regulators, and practitioners further along the way of these promising new technologies.

Chapter 6, 7, and 8 deal with various forms of sustainable finance and as a contribution to the literature especially with its complementary side, namely corporate social irresponsibility and corporate scandals. The approach involves not only examining the desired form of sustainability, but also considering its complement, which should be avoided. This dissertation analyzes irresponsibility respectively corporate scandals in the context of mutual funds chapter 6, with respect to corporate payout policy in chapter 7, and in the context of prior outperformance measured in risk-adjusted returns in chapter 8. Although the datasets comprise around 20 years and international samples, it is likely that not all scandals, especially in the more distant past, are discovered. Since public awareness and the global connectivity rise, it is probable that a higher share of all scandals around the world are nowadays revealed. However, by using historical data, the problem of false zeros, meaning undetected but potentially scandalous corporate actions, for which there are statistical corrections employed within this dissertation, is still likely. However, the effects shown in these studies are probably more pronounced than found within the data. Therefore, future research could focus on better ways, for example using artificial intelligence, to discover discrepancies or even scandals within corporations and across the globe. As outlined within the introduction, the measurement of sustainability and therefore also the measurement of irresponsibility is still a matter of political as well as scientific debate. Missing or diverging definitions are not supportive for the common goal of a sustainable future. So besides the important research of the effects of sustainability, more and pronounced effort should be put into the merger and consolidation of definitions.

## 9.2 Outlook

As outlined herein, digital and sustainable finance are two important and driving factors for the economy in general, for capital markets, as well as in academic finance. The promises of digitization raise hope on the one hand for higher efficiency regarding capital markets, and on the other for technological innovation. However, technologies like the blockchain or artificial intelligence can also disrupt the traditional financial market. The blockchain, through its transparency, traceability and novel consensus mechanisms, offer decentralization and democratization of finance in general. The disintermediation of financial intermediaries in the context of these goals seems to be promising and at the same time questionable, as power dynamics and institutional trust may not be granted in the future. Still, illegal activities, fraud, missing trust, and lack of efficiency regarding energy consumption as well as convenience for investors may still hinder the adoption of the digital realm. However, the possibilities for innovation, application, and for future research seem endless and the progression in the digital era of finance cannot be stopped.

The direction of sustainable finance is difficult to predict. Although in recent times progress has been made in terms of the internalization of external costs, regarding definitions of terminologies, and concerning the measurement of sustainability and the complements thereof, the corresponding issues regarding economic competitiveness and preservation of welfare across nations seem to be difficult to solve. It is therefore the task of academia, to analyze and research which approaches and implementations are beneficial for social welfare gains and how these can be implemented within regulation and corporate practices alike. Although a majority of the general public is in agreement with the goals of a sustainable future, there is the need to convince the opposing side with rational and compelling arguments. Research and regulation need to go hand in hand in order to accomplish meaningful and agreed upon objectives. If the forces of free markets, prices, and their effects are then harnessed, a sustainable and prosperous future lies ahead of us.

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