Band 119

Sophia Bodensteiner

The Informational Value of Disaggregated Textual Sentiment in Real Estate Capital Markets

IRE|BS
International Real Estate Business School
Universität Regensburg

Schriften zu Immobilienökonomie und Immobilienrecht

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Die Deutsche Bibliothek – CIP Einheitsaufnahme
Sophia Bodensteiner
The Informational Value of Disaggregated Textual Sentiment in Real Estate Capital Markets
Regensburg: Universitätsbibliothek Regensburg 2026
(Schriften zu Immobilienökonomie und Immobilienrecht; Bd. 119)
Zugl.: Regensburg, Univ. Regensburg, Diss., 2026
ISBN 978-3-88246-557-0

ISBN 978-3-88246-557-0
© IRE|BS International Real Estate Business School, Universität Regensburg
Verlag: Universitätsbibliothek Regensburg, Regensburg 2026
Zugleich: Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft, eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg
Tag der mündlichen Prüfung: 10.07.2026
Berichterstatter: Prof. Dr. Wolfgang Schäfers
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Declaration on the Use of Artificial Intelligence (AI)

In the preparation of this dissertation, AI-assisted tools and large language models were used to improve spelling and grammar, and to support the linguistic optimization of my own wording. After using these tools, the content was independently reviewed and, where necessary, revised. I take full responsibility for the content of the submitted academic work. As of the time of writing, no official or specific guidelines of the Faculty of Business, Economics, and Real Estate of the University of Regensburg regarding the use of AI in dissertations have been adopted. Therefore, reference is made to the guidelines of the Faculty of Law of the University of Regensburg, dated May 7, 2025.

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1 Introduction

1.1 Motivation and Background

What distinguishes human from artificial decisions and opinions is the human ability to think, feel, and process information subjectively, shaped by individual experiences and beliefs. In the early 1900s, John Maynard Keynes (1936) referred to irrational actions and beliefs as "animal spirits". Since then, this concept has developed into the wider field of behavioral finance, which connects psychology and finance by focusing on individual-level biases that challenge the rational assumptions of the efficient market theory (Shiller, 2003; Hirshleifer, 2015). More recently, the field of "Social Economics and Finance" has emerged from this area of research, placing particular emphasis on interpersonal interaction and the influence of others (Hirshleifer, 2020; Han et al., 2022).

One core element of behavioral finance is that investors are subject to external opinions, resulting in investor sentiment (Baker and Wurgler, 2007). This sentiment can be extracted from surveys, market indices, or textual sources, the latter being referred to as textual sentiment analysis (Loughran and McDonald, 2011; Kearney and Liu, 2014). Textual sentiment has been shown to affect various equity and debt markets (Loughran and McDonald, 2011; Kearney and Liu, 2014; Wang, 2021; Schmeling and Wagner, 2025), as well as direct real asset markets (Clayton et al., 2009; Braun et al., 2020).

Real Estate Investment Trusts (REITs) represent an important intersection between private real estate and public capital markets and have become major investment vehicles and inflation-hedges (Clayton and MacKinnon, 2003; Muckenhaupt et al., 2025). Since the early REIT boom in the 1990s, the market capitalization of REITs has increased roughly 25-fold, reaching around 1.5 trillion US dollars by the end of 2025 (NAREIT, 2025). Their popularity reflects liquidity, diversification, income potential and access to real estate exposure without direct ownership. As indirect real estate markets grow in importance, the information mechanisms underlying price formation, capital allocation, and investor interpretation become increasingly relevant (Ling and Naranjo, 2015). This applies to both REIT equity and debt markets. While stock and bond investors evaluate the same firms, equity investors emphasize upside potential and growth, whereas bond investors focus on downside protection and default risk (Freybote, 2016; Kozak et al., 2026).

Although REIT markets are linked to the underlying real estate assets, they are not driven by asset and market fundamentals alone. Investor expectations and emotional responses also shape price formation. The impact of sentiment on indirect real estate markets has

been examined in various dimensions. In particular, the effect of textual sentiment on returns has been analyzed across different text channels, including news, social media, and corporate communication (Lin et al., 2009; Hausler et al., 2018; Ruscheinsky et al., 2018; Koelbl, 2020; Paulus et al., 2025), as well as across different investor types (Huerta et al., 2016; Freybote and Seagraves, 2017; Paulus et al., 2025). However, only few studies focus on REIT bonds and sentiment or on the differentiation between changing market regimes (Freybote, 2016; Freybote and Seagraves, 2018; Akinsomi, 2021), even though regular stock markets are strongly affected by sentiment during crises and across different regimes (Zouaoui et al., 2011; Taffler et al., 2025).

In recent years, financial markets have been challenged by geopolitical uncertainty, wars, and the COVID-19 pandemic. These external shocks have been accompanied by ongoing macroeconomic and financial changes, including inflation and interest rate spikes. In addition, the world is facing the climate crisis, which causes physical extreme weather events and affects companies through transition-related adjustments in financial and asset-specific policies. Against this background, the World Uncertainty Index (WUI) has risen by around 380% since the Global Financial Crisis (GFC) and reached all-time high values at the beginning of 2026 (Ahir et al., 2022; WUI, 2026). The World Sentiment Index (WSI) shows high volatility but, in contrast to the WUI, relatively stable positive values, with negative spikes during the GFC and the pandemic (WSI, 2026). While one might expect sentiment to be negative during challenging times, "irrational" optimism appears to dominate the index, possibly reflecting human expectations.

Taffler et al. (2025) show that economic narratives, investor emotions, and market prices are closely linked, especially during periods of heightened uncertainty. During such periods, investors tend to rely more strongly on herding behavior (Ampofo et al., 2023). Therefore, different regimes need to be analyzed separately and in greater depth. This dissertation provides closer insights into the REIT equity market during the COVID-19 pandemic and the REIT bond market during different interest rate cycles. These settings reflect broader structural breaks, and regime shifts in financial markets, in which the relevance of sentiment may increase.

While previous research has largely focused on rational, quantitative, and fundamental determinants of market outcomes, less attention has been paid to how softer and more subjective measures shape investor reactions. In this dissertation, the aim is to separate sentiment into fundamental and non-fundamental, or rational and irrational, components which can help identify the relevant drivers of financial markets and distinguish potentially informative communication from behavioral noise (Maurya et al., 2026). This distinction is

particularly important in real estate markets as they are not only an investment asset but also an emotionally charged good (Singh et al., 2023). In the case of REITs, the real asset exposure is transformed into a liquid vehicle. At the same time, the underlying assets remain heterogeneous, slow-moving, and difficult to value precisely. This combination creates room for expectations, narratives, and speculation and motivates a more granular view of sentiment in this dissertation. Aggregation is useful for simplicity, but it can blur economically meaningful heterogeneity and cross-sectional as well as time-varying differences. Especially in REIT markets, effects may differ across market environments, investor groups, and underlying asset classes (Carstens and Freybote, 2021; Liang et al., 2021).

Deepening REIT sentiment analysis is therefore highly relevant. To capture nuances in textual sources such as social media and corporate disclosures, advanced machine learning (ML) models are required. For the language processing component, large language models (LLMs) have become powerful tools. They are capable of dealing with context, ambiguity, and the complexity of casual, financial, or topic-specific language (Liu et al., 2019). Since sentiment, market regimes, and structural breaks are often associated with non-linearities and changes over time, advanced methods are further needed to identify these effects. Modern analytical algorithms make such analyses more feasible (Mullainathan and Spiess, 2017).

Overall, this dissertation aims to demonstrate that sentiment extracted from textual REIT sources must be separated at multiple levels in both equity and debt markets. By disaggregating sectors, ESG pillars, and sentiment components, it becomes possible to uncover meaningful differences in how investors value and react to sentiment. While doing that, accounting for different regimes is particularly important in economically uncertain times. In addition, non-linear relationships can reveal saturation, threshold, or reversal effects that conventional linear models may fail to capture. The dissertation addresses these aspects using modern ML tools for sentiment extraction, text filtering, and the decomposition of complex data structures.

1.2 Course of Analysis and Research Questions

This section gives a brief summary of the objectives and research questions in the three papers of the dissertation. The papers investigate how textual sentiment shapes pricing in U.S. REIT equity and debt markets using information from social media, corporate financial filings, and ESG reports.

Paper 1: Fundamentals or Noise? The Informative Value of Twitter Sentiment for REIT Returns

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This paper questions whether REIT-related Twitter sentiment reflects fundamentals about commercial real estate and capital markets or primarily captures irrational noise. Using Twitter data for U.S. REITs from 2014 to 2022, the study obtains optimistic, pessimistic, and overall sentiment measures and examines their relationship with macroeconomic, capital-market, and real-estate fundamentals. The COVID-19 pandemic is treated as a structural break to compare the pre-COVID and COVID periods. The paper first uses ARDL models to examine whether fundamental variables explain Twitter sentiment. It then decomposes sentiment into rational and irrational components and uses a VARX framework to analyze which component explains REIT returns. By splitting up the sentiment, this study aims to explain whether fundamental data or subjective noise drives REIT returns in different market regimes. Therefore, the following research questions are addressed:

- Does the explanatory power of fundamentals for REIT-related Twitter sentiment differ between the pre-COVID and COVID period?
- Is the relationship between REIT-related Twitter sentiment and REIT returns driven by rational, fundamentals-based sentiment or by irrational sentiment?
- Did the informative value of Twitter sentiment for REIT returns change during the COVID-19 pandemic?

Paper 2: Signals or Stories? ESG Sentiment and Investor Reactions in REIT Corporate Disclosure

Paper 2 analyzes whether ESG-related sentiment in the textual disclosures of U.S. equity REITs is reflected in stock market reactions. The study uses 10-K filings, 10-Q filings, and standalone ESG reports for 174 U.S. equity REITs from 2016 to 2025. Fine-tuned RoBERTa models are applied to identify ESG-related paragraphs, classify them into environmental, social, and governance pillars, and derive net positive tone measures. Event-study regressions then relate these sentiment measures to cumulative abnormal returns (CARs) around disclosure dates across several event windows. The analysis distinguishes between mandatory and voluntary disclosures and examines whether investor reactions differ across ESG pillars and REIT sub-sectors. The objective of this paper is to determine whether ESG-related language functions as a value-relevant signal or remains largely narrative in REIT corporate reporting, and to what extent disaggregation by pillar and REIT sub-sector reveals heterogeneous investor responses. The central research questions can thus be stated as follows:

- Is ESG-related sentiment in REIT corporate disclosures associated with CARs around disclosure events?
- Do investors react differently to ESG sentiment across disclosure channels and ESG pillars?
- How does the value relevance of ESG sentiment vary across REIT sub-sectors?

Paper 3: The Non-Linear Dynamics of Disclosure Tone and REIT Bond Yields

Finally, the third paper analyzes whether the relationship between disclosure tone in REIT financial statements and REIT bond yield spreads is non-linear and depends on whether tone is fundamentals-based or non-fundamental. Using 10-K and 10-Q filings from 64 bond-issuing U.S. equity REITs between 2011 and 2024, the study applies a fine-tuned RoBERTa model to derive net positive tone measures. These measures are analyzed using fixed effects panel regressions and an XGBoost model to test whether net positive tone has a quadratic relationship with future bond yield spreads. The study further separates tone into fundamentals-based and non-fundamental components by regressing tone on firm fundamentals and using the fitted values and residuals as separate explanatory variables. This approach aims to identify non-linearities in corporate disclosure sentiment based on the following research questions:

- Is the relationship between net positive disclosure tone in REIT financial statements and future REIT bond yield spreads linear, or does it follow a non-linear pattern?
- How do fundamentals-based and non-fundamental components of disclosure tone differ in their direction of effect on future REIT bond yield spreads?
- Does non-fundamental disclosure tone provide additional information to bond investors beyond observable firm fundamentals?

1.3 Co-Authors, Submissions, and Conference Presentations

This section provides an overview of co-authors, journal submissions, publication status and conference presentations.

Paper 1: Fundamentals or Noise? The Informative Value of Twitter Sentiment for REIT Returns

Authors:

Lukas Lautenschläger, Sophia Bodensteiner, Julia Freybote, Wolfgang Schäfers

Submission Details:

Journal: Journal of Property Research

Status: Revise and Resubmit

Conference Presentations:

This paper was presented at:

- the 40th Annual Conference of the American Real Estate Society (ARES) in Orlando, USA (2024)
- the 30th Annual Conference of the European Real Estate Society (ERES) in Gdansk, Poland (2024)
- the 31st Annual Conference of the European Real Estate Society (ERES) in Athens, Greece (2025)

Paper 2: Signals or Stories? ESG Sentiment and Investor Reactions in REIT Corporate Disclosure

Authors:

Sophia Bodensteiner, Lukas Lautenschläger, Wolfgang Schäfers

Submission Details:

Journal: Journal of Property Investment & Finance

Status: Under Review

Conference Presentations:

This paper was presented at:

- the 41st Annual Conference of the American Real Estate Society (ARES) in Tucson, USA (2025)
- the 31st Annual Conference of the European Real Estate Society (ERES) in Athens, Greece (2025)

Paper 3: The Non-Linear Dynamics of Disclosure Tone and REIT Bond Yields

Authors:

Hendrik Jenett, Sophia Bodensteiner, Julia Freybote, Wolfgang Schäfers

Submission Details:

Journal: Journal of Real Estate Research

Status: Revise and Resubmit

Conference Presentations:

This paper was presented at:

- the 32nd Annual Conference of the Pacific Rim Real Estate Society (PRRES) in Adelaide, Australia (2026)

This paper will be presented at:

- the 32nd Annual Conference of the European Real Estate Society (ERES) in Vienna, Austria (2026)

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2 Fundamentals or Noise? The Informative Value of Twitter Sentiment for REIT Returns

2.1 Abstract

Twitter sentiment has been found to predict REIT returns, which raises the question as to whether this is due to it containing fundamental information or merely representing noise. We hypothesize that the informative value of Twitter sentiment for REIT returns changed due to an increased engagement of individual investors with REITs during the COVID-19 pandemic. We extract sentiment measures from REIT-related Tweets over the period of 2014 to 2022 and assess 1) whether the explanatory power of fundamentals for Twitter sentiment differs between the pre- and COVID period and 2) whether the relationship of sentiment and REIT returns is driven by rational (fundamentals-based) or irrational sentiment. We find that fundamentals such as inflation, stock market returns, credit risk spread, individual stock investor sentiment and volatility have more predictive power for optimistic, pessimistic and overall Twitter sentiment in the COVID period than in the pre-COVID period. Furthermore, pessimistic Twitter sentiment has the highest explanatory power for REIT returns with irrational (rational) pessimistic Twitter sentiment predicting REIT returns in the pre-COVID (COVID) period. Our findings provide evidence for a structural break in the informative value of Twitter sentiment for REIT returns.

Keywords: REITs, Investor Sentiment, Individual Investors, Social Media, Textual Analysis

2.2 Introduction

Over the last decade, social media platforms such as Twitter, Seeking Alpha and StockTwits have increased in importance for the stock market investment community, particularly for individual (unsophisticated) investors (Eliner and Kobilov, 2023). Social media allows investors to observe, talk to as well as share their ideas and strategies with each other, which then can impact investment decisions (Han et al., 2020). This has led to a new paradigm, which Hirshleifer (2020) refers to as 'Social Economics and Finance'. It is distinct from paradigms such as behavioral finance or information economics and focuses on the impact of social media interactions on decision-making and investor behavior in financial markets. Understanding social economics and finance is important as social interactions of investors can lead to, amongst others, swings in economic sentiment and bubbles (social transmission bias; Hirshleifer, 2020).

Paulus et al. (2025) find that Twitter sentiment allows predicting aggregated REIT returns, which is in line with non-REIT studies that find social media sentiment to have informative value for stock returns, trading volume, and stock market liquidity (Ammari et al., 2023; Karampatsas et al., 2023; Gu and Kurov, 2020; Tan and Tas, 2021; Sul et al., 2017; Ranco et al., 2015). However, Paulus et al. (2025) fail to explain why Twitter sentiment predicts REIT returns. On the one hand, Twitter sentiment could reflect fundamentals that affect commercial real estate and REIT markets (rational or fundamentals-based sentiment). On the other hand, it could reflect irrationality or noise that impacts investor decision-making and REIT returns (irrational sentiment). This study uses Paulus et al. (2025) as a starting point to investigate what information Twitter sentiment contains and why it can explain REIT returns.

The REIT industry is uniquely suited for our investigation as it allows for a quasi-experimental design for the following reasons: Twitter users tend to focus on large cap stocks (Cookson et al., 2024) and popular stocks they are familiar with, such as Facebook, Netflix or Tesla (Welch, 2022). Furthermore, Twitter is a social media platform used rather for leisure comments than professional ones and more likely reflects users as consumers (Tang, 2018). Considering the REIT industry is less consumer-focused and highly specialized, its ability to attract the attention of a large share of unsophisticated investors on Twitter is likely limited. In fact, Zeitun et al. (2023) find that real estate industry-level returns have less sensitivity to changes in Twitter sentiment than returns of industries such as healthcare, consumer discretionary, and information technology.

However, individual investors gravitate toward attention-grabbing stocks (Barber and Odean, 2008), and during the pandemic, stocks that received a lot of COVID-related media

attention were traded more by these investors (Ozik et al., 2021). Considering that commercial real estate markets were heavily affected by COVID, ranging from a negative impact (e.g., office, hospitality) to a positive one (e.g., logistics), and the situation of landlords was extensively discussed in the media, more individual investors likely focused on REITs during the pandemic than before. Furthermore, the COVID period in the US was characterized by stay-at-home orders, relief cash payments to households and FinTech innovations such as Robinhood with commission-free trading, which increased the time individual investors were able to engage on social media and invest excess funds in the stock market. Welch (2022) finds that small retail investors using Robinhood collectively stayed calm at the beginning of the COVID period and purchased more stocks. Ozik et al. (2021) show that individual (retail) investors traded more on Robinhood when lockdowns went into effect. Furthermore, REITs were not only likely to get more attention from individual investors during the pandemic, but these investors also had more time to obtain information about the REIT industry and individual firms.

Consequently, we expect a structural break in the explanatory power of economic, capital and real estate market fundamentals for REIT-specific Twitter sentiment as well as the informative value of Twitter sentiment for REIT returns between the pre-COVID and COVID period. In particular, as our first hypothesis, we expect that fundamentals are able to predict Twitter sentiment to a higher degree in the COVID period than in the pre-COVID period. This follows the assumption that individual investors had more time and possibilities to access valuable information due to worldwide lockdowns. Furthermore, we hypothesize that the relationship of Twitter sentiment and REIT returns in the pre-COVID period is driven by noise or irrationality (irrational Twitter sentiment), while it was driven by the rational (fundamentals-based) component of Twitter sentiment in the COVID period.

Using natural language processing and Twitter data over the period of 2014 to 2022, we follow Paulus et al. (2025) to extract optimistic, pessimistic and overall sentiment from tweets about REITs. Next, we investigate the relationship of each sentiment measure with macroeconomic, capital market and commercial real estate market variables to assess which type of fundamental information affects REIT-related Twitter sentiment. In the last step, we separate Twitter sentiment into a rational and irrational sentiment component to analyze 1) whether the relationship of Twitter sentiment and REIT returns is driven by fundamentals (rational sentiment), noise (irrational sentiment) or a combination of both and 2) whether this relationship changed during the COVID period.

We find that the explanatory power of macroeconomic and capital market fundamentals such as inflation, stock market returns, credit risk spread, individual stock investor sentiment and volatility is higher for optimistic, pessimistic and overall Twitter sentiment in the COVID period than in the pre-COVID period. Furthermore, we provide evidence that pessimistic Twitter sentiment, as opposed to optimistic or overall sentiment, has the highest explanatory power for REIT returns. Hereby, irrational pessimistic Twitter sentiment predicts REIT returns in the pre-COVID period, while rational (fundamentals-based) pessimistic Twitter sentiment predicts REIT returns in the COVID period.

Our study adds to the general finance and REIT literature in several ways. First, our study adds to a wider finance literature on social media and individual stock market investors (e.g., Cookson et al., 2024; Schmidt, 2020; Jame et al., 2016; Chen et al., 2014) by showing that the informative value of social media-based investor sentiment for stock returns can change over time, for example, due to individual investors becoming more informed about an industry. Our findings also emphasize the importance of separating sentiment measures into fundamental and non-fundamental-based components.

Compared to institutional REIT investor sentiment (e.g., Aroul et al., 2023; Carstens and Freybote, 2019; Das et al., 2015), the sentiment of individual REIT investors has been neglected in the REIT literature. One challenge of investigating individual REIT investor sentiment is the difficulty of obtaining data. Considering the heavy use of social media by individual investors, our REIT-specific Twitter-based sentiment measures represent a proxy for the sentiment of this type of investor. Additionally, our study is the first to investigate factors that drive individual REIT investor sentiment. As Twitter sentiment has been found to impact REIT returns (Paulus et al., 2025), insights into whether it is due to fundamental information or irrationality has practical implications for the investment and asset pricing decision-making of sophisticated REIT investors.

Our study has a few limitations due to data availability and access: First, we only focus on Twitter as a social media platform. Compared to other platforms such as SeekingAlpha or StockTwits, Twitter messages are shorter, which impacts their informative content (Cookson et al., 2024). Future studies with access to data from other social media platforms may use our findings as a starting point and investigate the informative value of other social media sentiment for REITs. Another limitation lies in the dataset, as it does not allow us to identify the user behind each tweet and further investigate their characteristics. Last, we are not able to extend our dataset to the post-COVID period due to the drastic change in Twitter API accessibility with its conversion to the X platform in early 2023.

The remainder of our study is structured as follows. Next, we review the relevant literature to provide a theoretical framework. It is followed by the discussion of our data and methodology as well as the presentation of our results and a conclusion.

2.3 Literature Review

2.3.1 Individual Investor Behavior

Several studies investigate individual (retail) stock market investors and show that the trading behavior of individual investors is characterized by overconfidence, herding, underperformance, and a focus on attention-grabbing stocks. Barber and Odean (2000) provide evidence that trading by individual investors reflects investor overconfidence and underperforms benchmarks. Barber and Odean (2002) investigate individual investor behavior after switching from phone-based to online trading. They show that after going online, investors traded more actively, speculatively and less profitably, which can be explained by overconfidence due to self-attribution bias and illusions of control and knowledge.

Barber and Odean (2008) show that individual investors focus on buying attention-grabbing stocks such as stocks featured in the media or stocks with extreme one-day returns. This tendency results from bounded rationality, lower sophistication and limited attention of individual investors when deciding on which stocks to buy from a large selection of possible options. The selling behavior of individual investors, however, is less affected by attention-grabbing stocks. On the other hand, professional investors such as professional money managers are less likely to buy attention-grabbing stocks. Da et al. (2011) develop an attention measure based on Google searches to investigate the focus of individual investors on attention-grabbing stocks. They provide evidence that this measure captures individual investor attention, primarily of less sophisticated ones, and can predict stock price developments and IPO returns. Kumar (2009) shows that, in contrast to institutional investors, certain individual investors prefer lottery-type stocks, particularly in deteriorating economic conditions. Individuals investing in lottery-type stocks are relatively unsophisticated and more likely to spend funds on state lotteries.

Social media, mobile internet and FinTech innovations further promote individual investor behaviors such as herding. While Barber and Odean (2008) investigate attention-grabbing events that influence individual investor trades by focusing on news, trading volume and previous stock returns. The authors acknowledge that chat rooms or word of mouth represent other ways in which stocks can grab the attention of individual investors. Barber et al. (2009) provide additional evidence for individual investor herding. Barber et al. (2022) show that Robinhood investors are more likely to engage in trading high-attention stocks

than other individual investors, which can be explained by the low levels of sophistication of investors using Robinhood and its features, as well as herding. The trading behavior of Robinhood users can forecast abnormal returns.

However, Kelly and Tetlock (2013) and Kaniel et al. (2012) provide evidence that individual investor trades can also contain fundamental and private information. One explanation is that individual investors understand consumer preferences or have knowledge of a particular company due to employee relationships or geographical proximity (Kelly and Tetlock, 2013). Another is that even if individual investors have imprecise information, the aggregation of their trades may yield valuable information (Kaniel et al. 2012). A third explanation is that individual investors learn over time and improve their abilities while others acknowledge their insufficiencies and cease to actively trade (Seru et al., 2010).

2.3.2 Individual Investors and Social Media

Individual investors have a variety of information sources such as news, friends & family, brokers, analysts or investment newsletters and other publications. Social media represents an additional source of information, which increased in importance for individual investors over the last years (Eliner and Kobilov, 2023). An emerging finance literature investigates the question of how valuable information from social media is: Does it just represent cheap talk and naïve investor reactions or contain decision-relevant information for stock market investors?

Schmidt (2020) shows that the sharing of trustworthy investment information on social media depends on the investment horizon of investors. Short-term investors with long-term information have an incentive to share correct information (reliable stock tips) while long-term investors have an incentive to disseminate incorrect or valueless information (cheap talk). Jame et al. (2016) focus on the use of social media as a source of information and investigate crowdsourced earnings forecasts from Estimize. They show that these forecasts have informative value for future earnings and capture the market's expectations. Hereby, a larger number of contributors improves the informative value. The authors provide evidence that social media and crowdsourced information represent an alternative source of information for the stock market. Sprenger et al. (2014) use Twitter messages to identify firm-specific good and bad events and provide evidence that they reflect relevant news events.

Cookson et al. (2024) show that differences in social media platform (Twitter, StockTwits and Seeking Alpha) in terms of length of messages and users can lead to variations in the relevance of social media-generated information. Furthermore, they find that the

information (signal) in social media is distinct from traditional media. Cookson and Niessner (2020) find that the language on social media (StockTwits) is influenced by prominent investors, and that information diffuses slowly from sophisticated to unsophisticated users over time. Focusing on SeekingAlpha, Chen et al. (2014) investigate how investor opinions on social media affect stock returns and earnings surprises. They show that negative words on social media contain value relevant information beyond what is provided by financial analyst and provide evidence for the wisdom of crowds.

2.3.3 Twitter Sentiment and Stock Market Fundamentals

An emerging literature focuses on social media sentiment and its informative value for stock market fundamentals at the aggregated or disaggregated level. One set of studies investigates firm-level Twitter sentiment: Ranco et al. (2015) extract firm-specific Twitter sentiment and find that financial Twitter data has a relationship with abnormal stock returns, depending on Twitter volume. Tan and Tas (2021) provide evidence that firm-specific Twitter sentiment predicts trading volume for US and international companies. The authors show that social media sentiment has informative value for stock returns, which is independent of news sentiment. They conclude that social media sentiment represents an additional source of information for developing trading strategies.

Sul et al. (2017) distinguish firm-specific Twitter sentiment into positive and negative and find that both types of sentiment have informative value for future stock returns. In particular, they show that a trading strategy based on Twitter sentiment can yield meaningful economic returns. Gu and Kurov (2020) show that Twitter sentiment has predictive value for stock returns, which can be partly explained with sentiment providing new information about analyst recommendations, price targets and quarterly earnings. Karampatsas et al. (2023) find that firm-specific Twitter and StockTwits sentiment have a relationship with abnormal stock returns during negative earnings surprises, particularly for firms that are difficult to value and arbitrage. Ammari et al. (2023) investigate Twitter sentiment and stock market liquidity during the COVID period and find that the pandemic changed the relationship of sentiment and liquidity.

Other studies focus on Twitter sentiment in the context of individual industries and/or financial indices: Reboredo et al. (2018) focus on Twitter sentiment in the context of renewable energy stock and find no impact on returns, volatility and trading volumes, which suggests that the wisdom of the crowd has no pricing effects for this industry. However, Twitter sentiment creates feedback effects for volatility and trading volume. The authors identify correlations between Twitter sentiment and financial indices. Zeitun et al. (2023) focus on multiple industries and find that changes in Twitter sentiment have a larger

impact on the healthcare, communications, material, consumer discretionary, energy, staples and information technology sector than other industries such as financial, real estate, industrial and utilities.

Paulus et al. (2025) is the first study to investigate Twitter sentiment in the context of REITs. In line with previous non-REIT studies, they show that Twitter sentiment predicts aggregated REIT returns. However, the authors fail to investigate why Twitter sentiment has explanatory power for REIT returns. Twitter sentiment may contain fundamental information, which in turn explains its informative value for REIT returns. It may also contain noise (irrationality), which affects REIT returns. The relationship of Twitter sentiment and REIT returns could also be driven by a combination of fundamental information and noise.

The finance literature on individual investors is divided on whether this type of investor represents unsophisticated noise traders prone to behavioral biases (e.g., Barber, 2009; Barber and Odean, 2000, 2002) or investors trading on fundamental information that learn by trading (Kelly and Tetlock, 2013; Kaniel et al., 2012; Seru et al., 2010). We firstly hypothesize that fundamentals have a higher explanatory power for REIT-specific Twitter sentiment in the COVID period as opposed to the pre-pandemic period. During the pandemic, commercial real estate received a lot of attention from the media, which likely increased the attention REITs received from individual investors. In times of lockdowns and COVID financial support, these individual investors had more time to research stocks and increase their understanding of the REIT industry and its fundamentals. As a result, we also expect the rational (fundamentals-based) component of Twitter sentiment to have a higher explanatory power than irrational Twitter sentiment for REIT returns in the COVID period. On the other hand, considering that individual users as captured by Twitter users are expected to be less familiar with REITs in the pre-pandemic period, we hypothesize that the relationship of Twitter sentiment and REIT returns was driven by irrationality in this period.

2.4 Data and Methodology

2.4.1 Derivation of Twitter Sentiment Measures

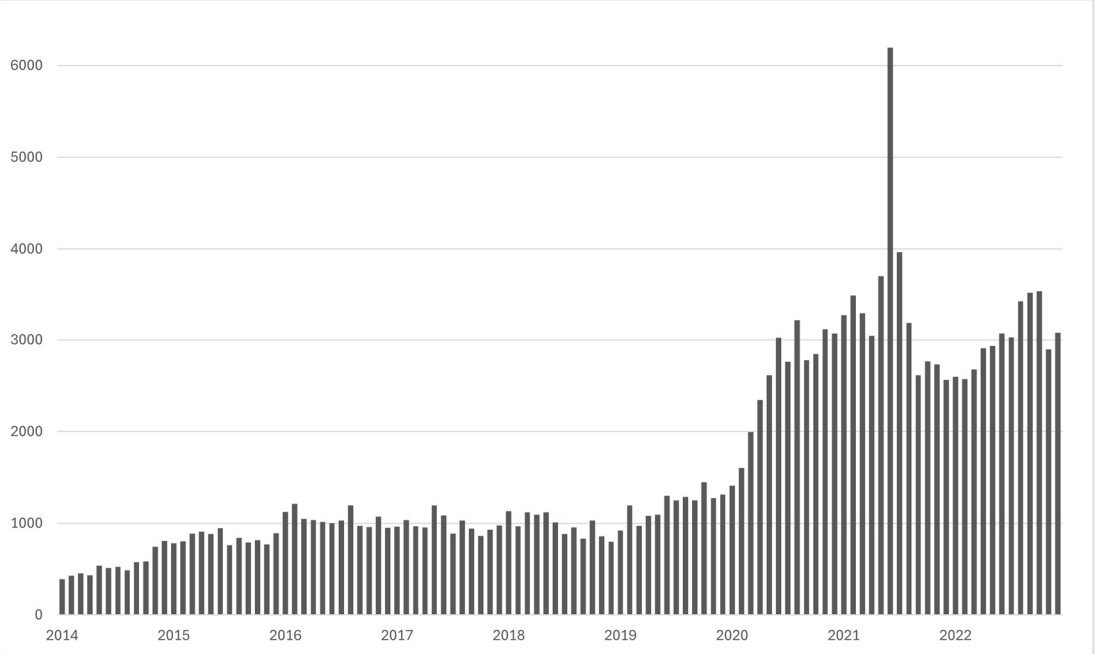
To derive our Twitter sentiment measures, we collected textual data using the Tweepy API for Python with the firm identifiers or names of U.S. REITs as search parameters over the period of January 2014 to December 2022. The initial dataset consists of about 3.9 million tweets before data cleaning. As Twitter messages can be categorized as informal

language, it is necessary to apply extensive natural language processing techniques in order to derive their correct sentiment (e.g. Ankit and Saleena, 2018; Dorle and Pise, 2018).

We follow the approach employed by Paulus et al. (2025) to pre-process and filter the Twitter data: We convert all words to lowercase, followed by the conversion of slang terms to their formal counterparts by utilizing the Internet & Slang Dictionary from www.noslang.com, consisting of over 5,000 slang terms (Jones, 2022). Further, we expand contractions such as "isn't" to "is not". To address the unique characteristics of the language used on Twitter, mentions signalized by "@word", cashtags "$word" and hashtags "#word", retweets, links/URLs, emojis and non-ASCII symbols are removed. Additionally, numbers and punctuations are taken out of the textual corpus. The final pre-processing step applied is lemmatization to transform the words into their root forms reducing the complexity and size of the vocabulary of the textual data (Paulus et al., 2025; Manning et al., 2008).

In the derivation of our Twitter sentiment measures, we place particular emphasis on the selection process to minimize irrelevant messages in the textual corpus. After excluding simple retweets and messages without interactions, duplicate messages are eliminated in two steps: First, messages that are identical are filtered out. Second, messages that are mostly identical, indicating automated spam during the same day are removed based on their word sequences. The temporal restriction minimizes the risk of removing relevant tweets that coincidentally share the same word sequence. Last, we use the Global Vector (GloVe) and cosine similarity approach for further filtering the textual data to increase its relevance to the REIT market (Paulus et al., 2025). Following this approach, we create and combine multiple lists of signal words related to REIT-related phrases to achieve a more extensive and simultaneously relevant list compared to Paulus et al. (2025). As the unfiltered Twitter data contains messages related to cryptocurrency or other digital asset-related content, we repeat this process and create word lists related to these topics. By only including tweets that contain at least one word with a REIT context and no phrase from the other word lists, we avoid the inclusion of leftover irrelevant messages. The final dataset contains 175,130 remaining messages. As shown in Figure 2.1, the monthly REIT-specific Twitter message volume sharply increased with the start of the COVID pandemic. This provides support for our argument that REITs received an increased attention from individual investors during the pandemic period, as suggested by an increased activity with regards to REIT-specific Tweets.

Figure 2.1 REIT-Specific Twitter Message Volume per Month



Note: The figure shows the monthly REIT-specific Twitter Message Volume over the period from January 2014 to December 2022 after applying our filter process. The y-axis represents the absolute monthly number of Tweets, while the x-axis denotes the timeline in years. A steady upward trend is observable from 2014 through 2019, followed by a pronounced increase beginning in early 2020. After the peak in early 2021, the values stabilize at an elevated level with continued fluctuations.

We derive our Twitter sentiment measures based on the cleaned Twitter data using the RoBERTa (Robustly Optimized BERT Pretraining Approach) model by Liu et al. (2019), which is an improved version of BERT (Bidirectional Encoder Representations from Transformers), introduced by Devlin et al. (2019). These models are Large Language Models (LLM) and represent one of the state-of-the-art approaches in natural language processing (Karanikola et al., 2023). It is noteworthy that the GPT model on which the industry-disrupting ChatGPT is based on (Brown et al., 2020) falls under the LLM approach. Additionally, the usage of the RoBERTa model minimizes the necessity to obtain an adequate training dataset as the model comes pre-trained and is only optimized in relation to an individual use case (Liu et al., 2019). Paulus et al. (2025) find more sophisticated classifiers to yield better performance for sentiment analysis, we expect the RoBERTa model to provide an even more accurate representation of the true sentiment embedded in Twitter messages. Our approach to using RoBERTa for sentiment classification results in a probabilistic output with values between 0 and 1, where values close to 0 indicate a low probability of a message being positive and vice versa. To achieve a three-way classification, we deploy a decision rule to achieve a three-level sentiment classification in line with Paulus et al. (2025) given as:

$$P \geq 0.667 \rightarrow \text{positive sentiment}$$

$$0.333 < P < 0.667 \rightarrow \text{neutral sentiment}$$

$$P \leq 0.333 \rightarrow \text{negative sentiment}$$

After classifying the Twitter data, we aggregate it on a monthly frequency to construct three Twitter sentiment measures in line with previous studies (e.g., Paulus et al., 2025; Ruscheinsky et al., 2018; Hausler et al., 2018). The first measure, the Optimism Indicator (*OI*), is based on Antweiler and Frank (2004) and captures the overall optimism expressed in the messages. The *OI* is defined as shown in Equation 2.1.

$$OI_t = \frac{\sum_1^I \text{ positive messages }_{i,t}}{\sum \text{ total number of messages }_t} \tag{2.1}$$

Acting as the reciprocal of the *OI*, the second measure, the Pessimism Indicator (*PI*), measures the total amount of negative messages in relation of the total number of messages as shown in Equation 2.2. It is based on the idea of a negativity bias as proposed by Rozin and Royzman (2001), who stated an increased effect of negative influences in comparison to positive ones.

$$PI_t = \frac{\sum_1^J \text{ negative messages }_{j,t}}{\sum \text{ total number of messages }_t} \tag{2.2}$$

The third sentiment measure derived is the Sentiment Quotient (*SQ*) and measures the ratio of positive messages to the sum of positive and negative messages as shown in Equation 2.3.

$$SQ_t = \frac{\sum_1^I \text{ positive messages }_{i,t}}{\sum_1^I \text{ positive messages }_{i,t} + \sum_1^J \text{ negative messages }_{j,t}} \tag{2.3}$$

For all three measures, *i* represents a positive classified message, *j* a negative message and *t* the aggregated time frame.

2.4.2 Macroeconomic, Capital and Real Estate Market Variables

We obtain the following macroeconomic, capital and commercial real estate market variables over the period of 2014 to 2022. These variables are on a monthly basis to balance the short-term and quick-reacting nature of the stock market and the slower-changing underlying real estate market. Furthermore, this ensures capturing the true change in value of the underlying companies as these can only be seen in the long term,

as the short-term speculative asset prices are almost random walks on a day-to-day basis (Shiller, 2017).

To capture macroeconomic conditions, we obtain the monthly U.S. inflation (*INFLATION*) as well as the unemployment rate (*UNEMP*) from the U.S. Bureau of Labor Statistics. Furthermore, stock and bond market conditions may drive Twitter sentiment. Consequently, we obtain the monthly return on the S&P 500 index (*SP500*) to capture stock market conditions and the monthly spread between Moody's seasoned Baa- and Aaa-rated corporate bonds (*SPREAD*) to capture bond market conditions from S&P Global and the Fed St Louis. Considering that Twitter sentiment reflects individual investor sentiment, it may also be affected by general stock market sentiment, as proxied by the monthly American Association of Individual Investors (*AAII*) bearish sentiment, or the volatility in the stock market, as proxied by the monthly CBOE Volatility Index (*VIX*). Last, the sentiment of Twitter users about REITs may be influenced by the performance of commercial real estate markets. We capture these conditions with the US composite of the CoStar Commercial Repeated Sales Index (*CCRSI*). In line with Paulus et al. (2025), we use the total return on the FTSE/NAREIT All Equity REIT index for our analysis of the relationships of rational and irrational Twitter sentiment with REIT returns. Our study hereby differs from Paulus et al. (2025), who use the total return on the FTSE/NAREIT All REIT index, which also includes mortgage and hybrid REITs.

We test for the presence of a unit root in our time series data using the Augmented Dickey-Fuller Test (ADF). To ensure the required stationarity, uniformity, and ease of interpretation, all variables are considered as first differences or growth rates. Additionally, we conduct tests for serial correlation and heteroscedasticity and apply Newey and West (1987) standard errors to increase robustness against those and statistical validity. Table 2.1 presents the descriptive statistics for our sentiment measures and fundamental variables.

Table 2.1 Descriptive Statistics

Panel A: Pre-COVID period					
	Min	Max	Mean	Median	Std_Dev
NAREIT	-0.079	0.116	0.010	0.010	0.037
OI	0.520	0.692	0.586	0.582	0.037
PI	0.107	0.237	0.181	0.183	0.026
SQ	0.687	0.866	0.764	0.765	0.035
UNEMP	0.035	0.067	0.047	0.047	0.009
INFLATION	-0.002	0.029	0.016	0.017	0.008
SP500	-0.092	0.083	0.008	0.010	0.033
SPREAD	0.550	1.490	0.901	0.890	0.220
AAII	0.197	0.442	0.294	0.283	0.049
VIX	10.125	24.953	14.979	14.241	3.437
CCRSI	141.893	230.276	188.060	186.404	27.675
Panel B: COVID period					
	Min	Max	Mean	Median	Std_Dev
NAREIT	-0.187	0.096	0.002	0.017	0.066
OI	0.399	0.576	0.524	0.535	0.036
PI	0.169	0.319	0.217	0.211	0.029
SQ	0.556	0.768	0.707	0.714	0.042
UNEMP	0.035	0.148	0.058	0.047	0.028
INFLATION	0.001	0.091	0.047	0.054	0.031
SP500	-0.125	0.127	0.007	0.022	0.062
SPREAD	0.650	1.700	0.940	0.900	0.260
AAII	0.225	0.543	0.383	0.400	0.096
VIX	16.957	57.737	25.117	23.299	7.633
CCRSI	231.056	307.702	268.269	265.382	27.822

Note: The table presents the descriptive statistics for the pre-COVID period (01/2014 - 01/2020) and the COVID period (02/2020 – 12/2022). NAREIT represents the monthly Total Return of the FTSE/NAREIT All Equity index. OI is the monthly Twitter optimism indicator, PI the pessimism indicator and SQ as the sentiment quotient reflects the general sentiment. INFLATION is the monthly inflation and UNEMP is the monthly unemployment rate in the US. SP500 represents the general stock market as the monthly return on the S&P 500 index. SPREAD is the monthly spread of Moody's seasoned Baa- and Aaa-rated corporate bonds, AAII is the monthly general stock market sentiment measured by the American Association of Individual Investors and VIX is the stock market volatility proxied by the CBOE Volatility Index. CCRSI is the monthly CoStar Commercial Repeated Sales Index. The values are shown as level data.

Considering we expect a structural break in the relationship of Twitter sentiment and REIT returns as a result of the COVID-19 pandemic, we separate our sample into two periods: The pre-COVID period is defined as January 2014 to January 2020 and the COVID period covers February 2020 to December 2022. The longer time horizon of the pre-crisis period enables a stabilized market overview under normal conditions.

2.4.3 Estimation

Our empirical investigation has two components: First, we assess the relationships of fundamental variables with optimistic, pessimistic and overall Twitter sentiment to determine their informative value for Twitter sentiment. Second, we separate sentiment measures into rational and irrational components and investigate their relationships with aggregated REIT returns.

For the first part, we use the sentiment measures, *OI*, *PI* and *SQ* as dependent variables, and fundamental variables as independent variables, separated by pre-COVID and COVID period. As we expect an immediate impact of Twitter sentiment due to the platform's quick-moving nature, we assume a non-lagged relationship between fundamental variables and Twitter sentiment. To achieve the needed flexibility to account for such a non-lagged relationship as well as to address endogeneity, we employ an autoregressive distributed lag (ARDL) model as shown in Equation 2.4. To simplify the model selection process, we assume the lag order of the autoregressive component and the independent regressor to be constant.

$$y_t = \alpha + \sum_{i=1}^{l} \phi_i \, y_{t-i} + \sum_{i=1}^{l} \beta_i \, x_{t-i} + u_{1t} \tag{2.4}$$

with y_t resembling one of the three sentiment measures (*OI, PI, SQ*) and x_t as one of the respective fundamental variables (*UNEMP, INFLATION, SP500, SPREAD, AAII, VIX, CCRSI*).

We employ statistical tests such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Final Prediction Error (FPE) to select an appropriate lag order. To ensure comparability, the lag order within the stated sets of regressions is kept consistent. Therefore, we determined the optimal lag order for each regression of the sets individually and compared them. The optimal lag order for the regressions within these sets was mostly unambiguous. If it was not, we utilized a majority voting system for each set.

For the second part of our empirical analysis, we extract the rational and irrational component of the Twitter sentiment using an orthogonalization approach based on Ling et al. (2014). In particular, we first regress the Twitter sentiment measures on our fundamental variables (*UNEMP, INFLATION, SP500, SPREAD, AAII, VIX, CCRSI*) and retain the fitted values. This represents the rational component of Twitter sentiment (*OI, PI, SQ*) that can be explained by macroeeconomic, capital market and commercial real estate market conditions. The residuals from these regressions represent the irrational components of Twitter sentiment as they are not explained by fundamentals but rather other factors such as irrationality.

Considering that the impact of rational and irrational Twitter sentiment on REIT returns is not likely immediate, it is not necessary to include non-lagged values for this analysis. Therefore, we employ a VARX model as shown in Equation 2.5. The VARX represents an extended form of the regular VAR model suitable for when control variables are included. We include a set of control variables in our time series analysis in line with Brooks and

Tsolacos (2010) to increase the robustness of our results. In particular, we control for macroeconomic conditions that impact REIT returns such as inflation and unemployment rate. We also include the US Economic Policy Uncertainty Index (*UNCERTAINTY*) (Baker et al., 2024) as policy uncertainty, especially during a crisis, can impact commercial real estate markets and thus REIT returns. Furthermore, we control for debt capital market conditions impacting REIT market conditions by including *SPREAD* and the difference between the 10-year Treasury bond yield and the three-month Treasury bill (*TERM*) in line with previous studies (Paulus et al., 2025; Braun et al., 2020; Hausler et al., 2018; Freybote and Seagraves, 2017; Clayton et al., 2009; Lin et al., 2009; Hoesli et al., 2008).

$$y_t = A_0 + \sum_{i=1}^{l} A_i \, y_{t-i} + BZ_t + u_{1t} \tag{2.5}$$

with the vector *Z* for the exogenous variables.

The lag order selection process for the VARX models follows the process described previously. To ensure further comparability, the lag order is determined for the regression using the aggregated sentiment before orthogonalizing and then also applied to the derived components. Additionally, we introduce a minimum lag order of six months to ensure capturing potential long-term relationships, as found by Paulus et al. (2025). Lastly, we use Granger causality tests, which test the joint significance of two lagged endogenous variables (Granger, 1969), to assess whether one variable in our VAR model predicts the other variable suggesting a cause-and-effect relationship between the two (Jalil and Rao 2019).

2.5 Results

2.5.1 Twitter Sentiment and Fundamental Variables

Table 2.2 presents the results for inflation and unemployment based on the model in Equation 2.4 separated by pre-COVID and COVID period. In the pre-COVID period, inflation has no explanatory power for REIT-specific Twitter sentiment, irrespective of the measure used (*OI, PI, SQ*). In the COVID period, inflation predicts optimistic, pessimistic and overall Twitter sentiment in multiple lags, however, the directionality of this relationship is ambiguous as signs vary. In particular, inflation has a negative and positive relationship with optimistic, pessimistic and overall REIT-specific Twitter sentiment respectively in different lags. This pattern shows an immediate reaction with changing signs in lagged values. This reverse effect could be interpreted as an overreaction first and correction

movement later. This dynamic could also be attributed to an increased awareness of individuals and a more pronounced impact of inflation during the COVID period. In the pre-COVID period, inflation in the US was stable and moderate, whereas inflation rates increased dramatically during the pandemic due to supply chain disruptions, increased consumer demand and higher energy prices.

The unemployment rate has limited informative value for optimistic, pessimistic and overall Twitter sentiment in either period. It is noteworthy that the direction of significant coefficients flips between the pre-COVID and COVID period. For example, unemployment has a significantly negative coefficient (first lag), albeit only at the 10% level, for *SQ* in the pre-COVID period, but a significantly positive coefficient (second lag) in the COVID period.

Table 2.2 ARDL Results for Twitter Sentiment, Inflation and Unemployment Rate

Panel A: Inflation						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.003	0.009**	0.001	-0.005**	-0.002	0.009**
$Sentiment_{t-1}$	-0.633***	-0.634***	-0.451***	-0.668***	-0.495***	-0.63***
$Sentiment_{t-2}$	-0.37***	-0.163*	-0.36***	-0.164**	-0.37***	-0.145*
$Sentiment_{t-3}$		0.005		0.037		0.02
$INFLATION_{t-0}$	-0.976	1.335**	1.081	-2.023***	-1.44	2.486***
$INFLATION_{t-1}$	-1.187	-0.894	0.118	1.032***	-0.446	-1.449***
$INFLATION_{t-2}$	1.932	-0.474	-1.383	0.401	1.947	-0.563
$INFLATION_{t-3}$		-2.553***		2.216***		-3.091***
Adj.R^2	0.31	0.32	0.21	0.43	0.24	0.40
Panel B: Unemployment Rate						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.005*	0.003	0.005*	-0.002	-0.007*	0.003
$Sentiment_{t-1}$	-0.616***	-0.445**	-0.474***	-0.247	-0.516**	-0.268
$Sentiment_{t-2}$	-0.398***	-0.102	-0.348***	-0.119	-0.369***	-0.06
$UNEMP_{t-0}$	-2.09	-0.301	1.224	-0.163	-1.811	0.107
$UNEMP_{t-1}$	-0.372	-0.002	4.865**	0.077	-5.102*	0.015
$UNEMP_{t-2}$	-2.185	0.314***	2.603	-0.399***	-3.243	0.503***
Adj.R^2	0.29	0.11	0.23	0.2	0.24	0.16

Note: This table shows the results of autoregressive distributed lag models (ARDL). In Panel A, the market fundamental variable inflation (INFLATION) is regressed on the different sentiment measures OI, PI and SQ as the dependent variables for the pre-COVID and COVID period. Panel B considers the unemployment rate (UNEMP) respectively. '***', '**' and '*' denote significance at the 1%, 5% and 10% level.

The results for stock and bond market conditions, as proxied by the S&P 500 return and credit risk spread respectively, are presented in Table 2.3. The return on the S&P 500 index has a negative (positive) relationship with optimistic and overall (pessimistic) Twitter sentiment in its first lag in the pre-COVID period. Thus, an increase in the S&P index return in the previous month predicts a decrease in the optimistic and overall REIT-specific sentiment of Twitter users and an increase in the pessimistic one. One explanation for this finding is that individual investors in this period considered REITs an alternative asset class to invest in when index funds and other stocks performed poorly. On the other hand, our

results for *SP500* in the COVID period are in line with expectations: An increase in the S&P 500 index return in the previous and current month predicts an increase (decrease) in the optimistic and overall (pessimistic) REIT-specific Twitter sentiment.

Corporate bond market conditions as proxied by the credit risk spread have no informative value for REIT-specific Twitter sentiment in the pre-COVID period. However, they predict Twitter sentiment in the COVID period in the expected directions: An increase in the credit risk spread in the current and previous month predicts a decrease (increase) in the REIT-specific optimistic and overall (pessimistic) Twitter sentiment. An explanation for this finding is that during the COVID period media reporting focused on tenant and landlord defaults to a larger degree, which in turn improved the understanding of individual investors as it relates to credit risk and REITs.

Table 2.3 ARDL Results for Twitter Sentiment, S&P 500 Returns and Credit Risk Spread

Panel A: SP500 Returns						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	0.001	-0.001	0.000	0.002	0.000	-0.002
$Sentiment_{t-1}$	-0.680***	-0.411***	-0.457***	-0.419***	-0.515***	-0.385***
$Sentiment_{t-2}$	-0.409***	-0.067	-0.394***	-0.030	-0.411***	-0.024
$SP500_{t-0}$	-0.126	0.165***	0.033	-0.167***	-0.072	0.225***
$SP500_{t-1}$	-0.304***	0.178**	0.138	-0.130**	-0.226***	0.188**
$SP500_{t-2}$	-0.031	0.051	-0.031	-0.018	0.022	0.031
Adj.R^2	0.36	0.23	0.21	0.33	0.25	0.31
Panel B: Credit Risk Spread						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.003	0.003	0.001	-0.002	-0.002	0.003
$Sentiment_{t-1}$	-0.642***	-0.623***	-0.427***	-0.627***	-0.474***	-0.602***
$Sentiment_{t-2}$	-0.381***	-0.250***	-0.330***	-0.228*	-0.344***	-0.209*
$SPREAD_{t-0}$	0.009	-0.072*	-0.065	0.056**	0.075	-0.082**
$SPREAD_{t-1}$	-0.008	-0.075***	0.063	0.046**	-0.073	-0.069**
$SPREAD_{t-2}$	-0.064	0.022	0.018	-0.020	-0.035	0.032
Adj.R^2	0.29	0.22	0.20	0.20	0.23	0.21

Note: This table shows the results of autoregressive distributed lag models (ARDL). In Panel A, the market fundamental variable SP 500 returns (SP500) is regressed on the different sentiment measures OI, PI and SQ as the dependent variables for the pre-COVID and COVID period. Panel B considers the credit risk spread (SPREAD) respectively. '***', '**' and '*' denote significance at the 1%, 5% and 10% level.

As shown in Table 2.4, the bearish individual investor sentiment (*AAII*) and volatility index (*VIX*) have no informative value for REIT-specific Twitter sentiment in the pre-COVID period with the exception of *AAII* and *OI*. In the COVID period, the general individual stock investor sentiment (*AAII*) predicts optimistic, pessimistic and overall Twitter sentiment. However, the directionality varies for *OI* and *SQ*. AAII bearish sentiment has a significantly negative coefficient for *OI* and *SQ* in the current or previous month and a significantly positive one for *PI* in the current month. Thus, an increase in bearish individual stock investor sentiment in the current or previous month, predicts a decrease in the optimistic

and overall Twitter sentiment and increase in the pessimistic one. It is noteworthy that the second lag for *AAII* in the *OI* and *SQ* regressions has a significantly positive coefficient, albeit only at the 10% level.

Table 2.4 ARDL Results for Twitter Sentiment, Stock Market Sentiment and Volatility

Panel A: AAII Bearish						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.003	0.003	0.002	-0.002	-0.003	0.003
$Sentiment_{t-1}$	-0.647***	-0.309**	-0.445***	-0.297**	-0.500***	-0.277***
$Sentiment_{t-2}$	-0.402***	0.056	-0.370***	0.061	-0.386***	0.079
$AAII_{t-0}$	0.012	-0.076	-0.061	0.089***	0.062	-0.109**
$AAII_{t-1}$	0.061	-0.066	-0.019	0.007	0.041	-0.029
$AAII_{t-2}$	0.117**	0.107	-0.065	-0.070	0.097	0.118*
Adj.R^2	0.31	0.18	0.20	0.22	0.23	0.20
Panel B: VIX						
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.003	0.000	0.002	0.001	-0.002	-0.001
$Sentiment_{t-1}$	-0.645***	-0.461***	-0.447***	-0.399***	-0.498***	-0.401***
$Sentiment_{t-2}$	-0.406***		-0.370***		-0.388***	
VIX_{t-0}	-0.001	-0.003***	0.000	0.003***	0.000	-0.004***
VIX_{t-1}	0.001	-0.002***	0.000	0.001**	0.000	-0.001***
VIX_{t-2}	0.001		- 0.001		0.001	
Adj.R^2	0.29	0.61	0.18	0.59	0.21	0.63

Note: This table shows the results of autoregressive distributed lag models (ARDL). In Panel A, the market fundamental variable stock market sentiment (AAII) is regressed on the different sentiment measures OI, PI and SQ as the dependent variables for the pre-COVID and COVID period. Panel B considers the VIX index (VIX) respectively. '***', '**' and '*' denote significance at the 1%, 5% and 10% level.

Our findings suggest that, to a certain degree, changes in individual stock investor sentiment, as captured by *AAII*, are mirrored by the REIT-specific sentiment of individual investors observed on Twitter. However, the explanatory power of *AAII* sentiment for the Twitter-based sentiment is relatively low. One explanation is that the *AAII* sentiment captures general stock market sentiment while our Twitter-sentiment captures REIT-specific sentiment of individual investors. Another explanation are the characteristics of individual investors responding to the AAII survey, which may be different from the characteristics of individual investors using Twitter (e.g., sophistication, experience, access to other data).

During COVID, the volatility index has a negative relationship with the optimistic and overall Twitter sentiment and a positive one with the pessimistic sentiment, which is in line with expectations. An increase in volatility in the stock market in the current and previous month predicts a decrease (increase) in the optimistic and overall (pessimistic) sentiment of Twitter users about REITs.

Last, we present the results for commercial real estate market conditions as proxied by the CCRSI index in Table 2.5. They suggest a limited informative value of commercial real estate market conditions for Twitter sentiment in the pre-COVID and COVID period. While one coefficient is significant for each sentiment measure and period with two being significant for *OI* in the COVID period, several are only significant at the 10% level. Furthermore, the results suggest that commercial real estate market conditions and Twitter sentiment have an inverse relationship, irrespective of period: An increase in commercial real estate prices in the current and/or previous two months predicts a decrease in the optimistic and overall REIT-specific Twitter sentiment and an increase in the pessimistic one. This may suggest that individual investors lack the sophistication with regards to commercial real estate markets to understand the effect of asset prices on REIT returns and profitability. Another possible explanation is that these investors consider high property prices in the direct real estate market an issue for the growth opportunities of REITs. While an investigation into the sophistication of individual REIT investors with regards to commercial real estate markets is beyond the scope of this study, future studies may use our findings as a starting point to further investigate these and other explanations.

Table 2.5 Results for Twitter Sentiment and Commercial Real Estate Prices

	CCRSI					
	Optimism Indicator (OI)		Pessimism Indicator (PI)		Sentiment Quotient (SQ)	
	preCOVID	COVID	preCOVID	COVID	preCOVID	COVID
Intercept	-0.005	0.017***	0.000	-0.011*	-0.001	0.017**
$Sentiment_{t-1}$	-0.628***	-0.376***	-0.472***	-0.429***	-0.506***	-0.386***
$Sentiment_{t-2}$	-0.404***	-0.099	-0.425***	-0.072	-0.431***	-0.066
$CCRSI_{t-0}$	0.003	-0.003*	-0.004	0.002	0.005	-0.003
$CCRSI_{t-1}$	-0.006*	0.001	0.008**	0.000	-0.010**	0.001
$CCRSI_{t-2}$	0.004	-0.004***	-0.003	0.003*	0.004	-0.004**
Adj.R^2	0.30	0.28	0.27	0.22	0.28	0.25

Note: This table shows the results of autoregressive distributed lag models (ARDL). The Commercial Real Estate Prices (CCRSI) is regressed on the different sentiment measures OI, PI and SQ as the dependent variables for the pre-COVID and COVID period. '***', '**' and '*' denote significance at the 1%, 5% and 10% level.

Overall, our results in Table 2.2 to 2.5 suggest that fundamental variables have limited explanatory power for optimistic, pessimistic and overall Twitter sentiment in the pre-COVID period. The informative value of fundamentals such as inflation, stock market returns, individual stock investor sentiment, volatility and credit risk spread for REIT-specific Twitter sentiment increased in the COVID period, which is in line with our expectations.

2.5.2 The Relationship of Rational and Irrational Twitter Sentiment and REIT Returns

Next, we investigate whether the relationship of Twitter sentiment and REIT returns in the pre-COVID and COVID period is driven by fundamentals (rational sentiment component), irrationality (irrational component) or both. We present our results for the respective rational and irrational component of the respective sentiment measure (*OI, PI, SQ*) in the pre-COVID period in Table 2.6. They suggest that primarily irrational pessimistic Twitter sentiment has explanatory power for REIT returns in this period. While the coefficient on the second lag of irrational *SQ* is significant, it is only at the 10% level. Furthermore, the coefficient on the fifth lag of rational *OI* is significant. Both results are likely of negligible substantial significance. On the other hand, rational pessimistic REIT sentiment has explanatory power for aggregated REIT returns in the COVID period (Table 2.7). An increase in the rational pessimistic Twitter sentiment in the previous two months predicts a decrease in REIT returns. While the coefficient on the second lag of rational SQ is significant, it is only at the 10% level.

Table 2.6 VAR Results for Rational and Irrational Twitter Sentiment and FTSE/NAREIT All Equity Total Return – Pre-COVID Period

	Optimism Indicator (OI)		**Pessimism Indicator (PI)**		**Sentiment Quotient (SQ)**	
	Rational	Irrational	Rational	Irrational	Rational	Irrational
Intercept	0.018***	0.019**	0.018***	0.019**	0.018***	0.019**
$NAREIT_{t-1}$	-0.293**	-0.331	-0.328**	-0.354*	-0.344***	-0.351
$NAREIT_{t-2}$	-0.021	-0.036	0.014	-0.030	0.002	-0.036
$NAREIT_{t-3}$	-0.161**	-0.195**	-0.135	-0.183**	-0.119	-0.195**
$NAREIT_{t-4}$	-0.269***	-0.342**	-0.303***	-0.333**	-0.319***	-0.345**
$NAREIT_{t-5}$	-0.146	-0.103	-0.169	-0.121	-0.138	-0.119
$NAREIT_{t-6}$	-0.049	-0.057	-0.062	-0.039	-0.070	-0.048
$Sentiment_{t-1}$	0.396	-0.168	0.294	0.241	0.055	-0.184
$Sentiment_{t-2}$	0.233	-0.108	-0.772	0.355**	0.605	-0.237*
$Sentiment_{t-3}$	-0.144	0.019	-0.139	0.247	0.080	-0.140
$Sentiment_{t-4}$	0.119	-0.091	0.868	0.340*	-0.374	-0.206
$Sentiment_{t-5}$	-0.671**	-0.154	0.619	0.276	-0.819	-0.195
$Sentiment_{t-6}$	0.537	0.063	0.249	0.241	0.014	-0.105
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.15	0.09	0.11	0.09	0.10	0.08
			Granger Causality			
Cause Sentiment	0.31	0.76	0.63	0.78	0.65	0.84
Cause Total Return	0.21	0.14	0.88	0.84	0.92	0.71

Note: This table shows the results for the vector autoregression models with exogenous variables (VARX). The models are tested for each sentiment measure (OI, PI, SQ) in the pre-COVID period (01/2014 - 01/2020). The sentiment has been separated in rational and irrational components using an orthogonalization approach based on Ling et al. (2014). The Total Return of the FTSE/NAREIT index and the sentiment measure each show the lagged results for the past 6 months. To control for external effects, the control variables INFLATION, UNEMP, UNCERTAINTY, SPREAD and TERM are integrated in the models. Besides the VAR models, the Granger Causality between the independent variable NAREIT and each sentiment measure is tested, and the respective p-values are presented. '***', '**' and '*' denote significance at the 1%, 5% and 10% level.

Table 2.7 VAR Results for Rational and Irrational Twitter Sentiment and FTSE/NAREIT All Equity Total Return – COVID Period

	Optimism Indicator (OI)		**Pessimism Indicator (PI)**		**Sentiment Quotient (SQ)**	
	Rational	Irrational	Rational	Irrational	Rational	Irrational
Intercept	0.007	0.004	0.006	0.015**	0.007	0.012*
$NAREIT_{t-1}$	-0.383**	-0.378***	-0.842***	-0.289*	-0.617**	-0.293*
$NAREIT_{t-2}$	-0.179	-0.049	-0.516**	0.286	-0.352	0.196
$NAREIT_{t-3}$	0.133	0.240	0.105	0.381*	0.124	0.318
$NAREIT_{t-4}$	0.632***	0.700***	0.723***	0.916***	0.677***	0.801***
$NAREIT_{t-5}$	0.144	0.345***	0.559	0.232**	0.330	0.241**
$NAREIT_{t-6}$	-0.657***	-0.290**	-0.428	-0.539***	-0.553*	-0.477***
$Sentiment_{t-1}$	-0.237	0.569	-1.553**	-2.103*	0.528	1.174
$Sentiment_{t-2}$	1.000	0.188	-1.522**	-0.526	0.977*	0.336
$Sentiment_{t-3}$	-0.108	-0.180	-0.432	0.652***	0.080	-0.444*
$Sentiment_{t-4}$	0.141	0.556	0.226	-0.569	-0.059	0.394
$Sentiment_{t-5}$	0.020	-0.090	0.523	-0.077	-0.127	0.029
$Sentiment_{t-6}$	1.311***	-0.038	-1.336**	0.194	1.021**	-0.133
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Adj. R^2	0.45	0.33	0.54	0.42	0.51	0.40
Granger Causality						
Cause Sentiment	0.35	0.68	0.14	0.41	0.21	0.47
Cause Total Return	< 0.01***	0.34	< 0.01***	0.87	< 0.01***	0.76

Note: This table shows the results for the vector autoregression models with exogenous variables (VARX). The models are tested for each sentiment measure (OI, PI, SQ) in the COVID period (02/2020 – 12/2022). The sentiment has been separated into rational and irrational components using an orthogonalization approach based on Ling et al. (2014). The Total_Return of the FTSE/NAREIT index and the sentiment measure each show the lagged results for the past 6 months. To control external effects, the control variables INFLATION, UNEMP, UNCERTAINTY, SPREAD and TERM are integrated in the models. Besides the VAR models, the Granger Causality between the independent variable NAREIT and each sentiment measure is tested, and the respective p-values are presented.'***', '**' and '*' denote significance at the 1%, 5% and 10% level.

Overall, our results in Table 2.6 and 2.7 suggest that pessimistic Twitter sentiment has the highest explanatory power for REIT returns. As hypothesized, irrational (rational) pessimistic Twitter sentiment predicts REIT returns in the pre-COVID (COVID) period. These findings also align with our findings for the higher explanatory power of fundamental variables for REIT-specific Twitter sentiment in the COVID period, compared to the pre-COVID, in Tables 2.2 to 2.5. Based on the 2013 to 2022 period, Paulus et al. (2025) find that pessimistic Twitter sentiment negatively predicts aggregated REIT returns. Our findings suggest that these results are driven by the COVID period and rational Twitter sentiment. The finding of pessimism being a superior sentiment indicator is also in line with previous studies that suggest a negativity bias due to investors being more influenced by negative information (e.g., Rozin and Royzman, 2001).

2.6 Conclusion

Over the last decade, social media such as Twitter has become an important source of information particularly for individual investors (Eliner and Kobilov, 2023). Paulus et al.

(2025) find that the sentiment of Twitter users about REITs can predict aggregated REIT returns. However, the authors fail to provide explanations for why Twitter sentiment can explain REIT returns. One explanation for the explanatory power of Twitter sentiment as a measure of individual investor sentiment is that it reflects fundamentals that impact REITs and their business. Another explanation is that Twitter sentiment reflects noise or irrationality of individual investors that affects REIT returns.

The question of why the sentiment of Twitter users, which are more likely individual investors, can predict returns of the highly specialized and less consumer-oriented REIT industry is interesting as individual investors tend to focus on large cap or popular stocks that they are familiar with as consumers (Cookson et al., 2024; Welch, 2022). Furthermore, individual investors tend to invest in attention-grabbing stocks (Barber and Odean, 2008). Historically, REITs were neither of these, and individual investors as a group likely had a lower familiarity with this industry.

However, during the COVID pandemic, positive or negative conditions in commercial real estate markets such as industrial, office, retail or hotel received more attention in the media and likely resulted in REITs receiving more attention from individual investors. In fact, Ozik et al. (2021) show that stocks, which received a lot of COVID-related media attention, were traded more by individual investors. Coupled with stay-at-home orders, which provided individual investors with more time to research industries and firms, as well as relief cash payments and FinTech innovations that made trading easier, the increased attention of the media on commercial real estate is expected to have led to a higher familiarity of individual investors with REITs in the COVID period. As a result, we hypothesize that in the pre-COVID crisis, the relationship of Twitter sentiment and REIT returns is driven by noise or irrationality. On the other hand, the increased sophistication of individual investors with REITs in the COVID period is expected to lead to fundamentals diving the relationship between Twitter sentiment and REIT returns in this period.

In our empirical investigation we employ a natural language processing approach to extract optimistic, pessimistic and overall sentiment measures from REIT-related Twitter comments over the period of 2014 to 2022. Next, we investigate the explanatory power of fundamental variables (macroeconomics, stock, bond and commercial real estate market) for the Twitter sentiment measures in the pre-COVID and COVID period using an autoregressive distributed lag (ARDL) model. Last, we decompose Twitter sentiment into a rational (fundamentals-based) and irrational component using an orthogonalization approach. We regress the sentiment measures on fundamentals and retain the fitted values (residuals) as rational (irrational) sentiment component. We then assess the explanatory

power of rational and irrational Twitter sentiment for REIT returns in the pre-COVID and COVID period using a VARX model.

In line with expectations, our findings show that the explanatory power of macroeconomic and capital market fundamentals such as inflation, stock market returns, credit risk spread, individual stock investor sentiment and volatility is higher for optimistic, pessimistic and overall Twitter sentiment in the COVID period than the pre-COVID period. We furthermore find that pessimistic Twitter sentiment, as opposed to optimistic or overall sentiment, has the highest explanatory power for REIT returns. In particular, irrational (rational) pessimistic Twitter sentiment predicts REIT returns in the pre-COVID (COVID) period.

Our findings provide evidence for a change in why Twitter sentiment can explain REIT returns. While it mostly captures noise in the pre-COVID period, the improved understanding of REITs by individual investors (Twitter users) lead to REIT-specific Twitter sentiment reflecting fundamentals in the COVID period. Our findings suggest that individual investors learned over time and increased their sophistication with regards to REITs. This is in line with previous studies, which find individual investors to also trade on fundamental information (e.g., Kelly and Tetlock, 2013; Kaniel et al., 2012) and learn to improve their abilities (Seru et al., 2010). Future studies may use our findings as a starting point to further investigate the understanding of commercial real estate markets and different property types by individual investors. The sophistication of these types of investors may vary across property types: Individual investors may have a better understanding of property types such as multifamily, hospitality and retail while their understanding is more limited with regards to industrial, office, agricultural or infrastructure. Additionally, while individual investors may have become more familiar with REIT stocks, their understanding of underlying commercial real estate markets, lease types, demand and supply drivers may still be limited.

Our study furthermore presents Twitter sentiment as a proxy for individual REIT investor sentiment, which has been under-researched in the literature. Future studies may investigate the relationship of institutional and individual REIT investor sentiment in more detail and their individual and joint effects on REIT market volatility, returns and trading behavior. These studies could investigate, for example, whether individual investors follow the more sophisticated institutional investors or whether these two types of sentiment are driven by different factors.

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3 Signals or Stories? ESG Sentiment and Investor Reactions in REIT Corporate Disclosure

3.1 Abstract

Purpose: This paper examines whether ESG-related sentiment in corporate disclosures of U.S. equity REITs is reflected in stock returns. It focuses on how investors respond to ESG language across disclosure channels, ESG pillars, and REIT sub-sectors.

Design / methodology / approach: We apply fine-tuned RoBERTa models to identify ESG-related text and classify sentiment in 10-K, 10-Q, and standalone ESG reports for 174 U.S. equity REITs from 2016–2025. Event-study regressions relate pillar-specific net positive tone measures to cumulative abnormal returns over multiple event windows.

Findings: Aggregate ESG sentiment shows limited explanatory power for abnormal returns, whereas disaggregated analyses reveal systematic differences across pillars and sectors. Environmental sentiment, especially in operationally intensive property types, exhibits the most robust positive association with cumulative abnormal returns, while social and governance sentiment display weaker or context-dependent effects.

Research limitations / implications: Results are conditional on the U.S. equity REIT universe, the 2016–2025 sample period, and the chosen LLM-based classification approach. Future research could examine alternative sentiment models, cross-country REIT samples, and interactions with regulatory changes in ESG disclosure.

Practical implications: For investors, the findings highlight that ESG language in REIT disclosures is most informative when focusing on environmental and, to a lesser extent, social sentiment in economically exposed sectors. For managers, they stress the importance of credible, financially linked ESG communication rather than generic ESG messaging.

Originality / value: The study is the first to combine LLM-based ESG sentiment extraction with event-study regressions for REIT disclosures, comparing mandatory and voluntary reports at pillar and sub-sector level. It shows that ESG communication is processed selectively rather than as a homogeneous signal in real estate capital markets.

Keywords: REITs, Corporate Disclosures, Sentiment, ESG, LLM, ESG reports

3.2 Introduction

In recent decades, environmental, social, and governance (ESG) considerations have become an increasingly important driver of corporate strategy and investment decisions worldwide. This development is particularly relevant in the real estate and built-environment sector, which accounts for a substantial share of global energy-related greenhouse gas emissions. With a market capitalization of around 1.47 trillion USD (NAREIT, 2025a) and being closely connected to direct real estate markets, real estate investment trusts (REITs) play a central role at the intersection of the sustainability challenges the real estate sector must face and financial markets (Robinson and McIntosh, 2022; Morri et al., 2024) and decarbonizing the economy (Tiwari and Miao, 2022; OECD, 2025). Their portfolio and investment decisions directly influence the environmental and social performance of the built environment, while their securities are continuously valued on public markets (Fan et al., 2024).

From an environmental perspective, REITs are directly exposed to both physical and climate transition risks. Physical risks such as extreme weather events, rising sea levels, and temperature fluctuations can affect asset values, disrupt operations, and reduce net operating income (NOI). At the same time, transition risks arising from stricter environmental regulations, carbon pricing, and changing tenant and investor preferences can increase compliance costs and capital requirements and potentially impact income streams and valuations (Contat et al., 2024). The social dimension of ESG has become increasingly important as well (Robinson and McIntosh, 2022; Zheng and Lee, 2026), particularly in connection with the heightened focus on diversity, equity, and inclusion (DEI) in the US. In the REIT context, social considerations operate on multiple levels. On the tenant side, factors such as health and safety, affordability, accessibility, and tenant satisfaction influence occupancy rates, lease renewals, and reputation. At the company level, workforce diversity, work practices, and employee well-being affect productivity, employee retention, and corporate culture. However, social factors are still difficult to measure and compare across firms. Therefore, comprehensive disclosure plays a crucial role in reporting on ‘S’. Governance is the third pillar of ESG and is particularly important for REITs due to their regulatory structure, agency issues, and dependence on debt capital. Effective governance mechanisms include transparent reporting, robust risk management, and conflict resolution frameworks. By doing so, companies can mitigate agency issues, reduce legal and regulatory risks, and protect themselves from reputational damage. Weak governance, on the other hand, can increase operational risks and undermine investor confidence (Zheng and Lee, 2026).

Given the growing importance of ESG information for investors, regulatory authorities have increasingly focused on disclosure requirements. The U.S. Securities and Exchange Commission (SEC) has recognized the importance of ESG-related risks and initially introduced mandatory ESG disclosure in 2024 (SEC, 2024). Although this decision has since been challenged and partially reversed due to shifted priorities in the beginning of 2025, it remains a hot topic in the regulatory debate (Tomlinson, 2025). In parallel, industry organizations such as the National Association of Real Estate Investment Trusts (NAREIT) have emphasized the importance of ESG transparency by providing reporting guidelines and frameworks tailored to REITs (NAREIT, 2025b). They argue that ESG best practices are not only beneficial to the environment and society but also improve long-term business performance and capital-market access.

Despite this, there is still limited empirical evidence on how ESG-related information in textual form is processed and evaluated by investors in the REIT sector. Existing studies are partly based on aggregated ESG scores, ratings or quantitative performance indicators (e.g. Aroul et al., 2022; Morri et al., 2024; Zheng and Lee, 2026), which may obscure important differences between environmental, social, and governance issues. Other REIT research shows that the individual pillars matter and behave differently: environmental issues are closely linked to asset characteristics and regulatory and transition risks (Morri et al., 2024; Fan et al., 2024), social issues relate to interactions with tenants, employees, and communities and affect operating results and reputation (Kim and Li, 2021; Carnini Pulino et al., 2022), and corporate governance is strongly shaped by the REIT-specific institutional framework and regulatory structure (Kohl and Schäfers, 2012; Zheng and Lee, 2026). Likewise, prior work on REIT disclosure documents that the narrative tone in financial reports contains value-relevant information for investors. The tone of earnings calls, MD&A sections, and forward-looking passages predicts short-term announcement returns and future operating performance (Doran et al., 2012; Koelbl, 2020; Carstens and Freybote, 2021). However, the specific role of ESG-related language and sentiment within these disclosures has been largely unexplored. It remains unclear whether investors distinguish between ESG statements in regulated financial reports and those in voluntary ESG or sustainability reports, whether aggregate ESG sentiment suffices, and how market reactions vary by ESG pillar and REIT sub-sector.

This study addresses these gaps by examining the value relevance of ESG-related sentiment in REIT disclosures. Focusing on U.S. equity REITs, we analyze ESG sentiment derived from both mandatory Form 10-K and 10-Q filings and voluntary ESG reports, allowing us to compare investor reactions across different types of disclosures. Specifically, we look at the cumulative abnormal returns (CARs) on the respective disclosure dates. We take a

disaggregated perspective on asset-class level and examine the environmental, social, and governance pillars separately to capture potential heterogeneities in investor reactions. To filter for ESG specific sections and to extract their sentiment, we use an advanced Large Language Model (LLM), which allows for a more nuanced language interpretation than traditional lexicon-based methods.

We aim to make several contributions to real estate literature with this study. First, it expands the growing body of research on ESG and REIT performance by shifting the focus from ESG performance scores and ratings to ESG communication and sentiment in textual disclosures. Second, it contributes to the literature on corporate disclosure and capital market reactions by providing evidence on how investors process ESG narratives in both mandatory and voluntary reporting. Third, by analyzing the pillar and sub-sector level, the study highlights the heterogeneity of ESG across different REIT asset classes and shows that environmental, social, and governance information are not uniformly priced. To our knowledge, we are the first to analyze ESG in corporate disclosure on a sub-sector level in the context of REITs. The rest of the paper is structured as follows: Section 3.2 provides an overview of the relevant literature and the development of the hypotheses. Section 3.3 describes the data and methodology. Section 3.4 presents the empirical results, and Section 3.5 contains the conclusion.

3.3 Literature Review and Hypotheses Development

3.3.1 Overall effect of ESG topics in corporate disclosure

ESG information has evolved into an essential component of corporate disclosure, as it is now systematically used by investors, analysts, and other stakeholders to assess firm value, risk, and long-term performance. It can reduce a company's cost of capital, attract ESG-oriented investors and thereby strengthens the link between ESG ratings and reports and financial performance. Additionally, it is linked to growth and investment opportunities (Chiang et al., 2019; Dhaliwal et al., 2012; Chen and Xie, 2022). Strong ESG or environmental performance is also associated with more flexible funding conditions, higher credit ratings and a positive relation to firm value (Eichholtz et al., 2019; Feng and Wu, 2023). ESG report characteristics such as readability, tone, length, and the use of numerical or forward-looking content help explain why some reports improve the information environment while others do not. More readable and higher-quality documents are associated with higher firm value and more accurate analyst forecasts (Muslu et al., 2019; Huang et al., 2025).

From a market-based perspective, ESG information is reflected in share prices and risk measures. Positive ESG news reduce stock-price crash risk, particularly for firms with low analyst coverage and weak transparency, and tend to generate moderate positive abnormal returns, while negative ESG news trigger much stronger negative reactions, with these effects shaped by firms' historical ESG records (Yu et al., 2023; Dorfleitner and Zhang, 2024; Jeong et al., 2025). Higher ESG ratings and active reporting about physical climate risks have also been associated with a lower risk of stock-price crashes, suggesting that ESG may offer partial protection against extreme negative events (Schiemann and Sakhel, 2019; Hunjra et al., 2020; Feng et al., 2022).

However, several recent studies caution against treating ESG as a solely positive driver. The disclosures can also have negative effects when claims are not backed by genuine performance improvements. Unsubstantiated or strategic "greenwashing" may lower firm value and trigger investor skepticism, especially in markets with heightened ESG scrutiny (Fatemi et al., 2018; Cerciello et al., 2023; Chacon et al., 2025). Very high ESG commitments can coincide with lower firm value, weaker operating cash flows, and heightened risk, suggesting overinvestment or immaterial ESG spending that is not compensated for by cash-flow gains. Beyond an optimal ESG level, further improvements in numerical ESG scores can be associated with weaker return performance (Morri et al., 2024; Kakinuma, 2025). Additionally, in the equity market, ESG-rated REITs have been found to underperform non-rated peers in returns (Neo et al., 2025).

Overall, the impact of ESG activities and their disclosure on firm value and risk is far from uniform and remains mixed and context-dependent across firms and information environments (Gillan et al., 2021). Meta-analytic evidence confirms that, on average, ESG engagement is associated with improved financial performance in real estate, albeit with substantial variation across market segments and pillars (Aroul et al., 2022; Morri et al., 2024; Zheng and Lee, 2026). Higher ESG quality also appears to work through real-economy channels, as better ESG performance is associated with higher rents and ESG-driven tenant demand for green buildings (Liu et al., 2025).

3.3.2 Sentiment analysis as a tool to assess ESG performance

One way to assess ESG performance in firm communication is to quantify qualitative information using sentiment analysis. Prior work shows that textual sentiment from news and social media predicts REIT market outcomes and that managerial tone in earnings calls, MD&A, and financial statements carries information about returns and operating performance (Doran et al., 2012; Hausler et al., 2018; Ruscheinsky et al., 2018; Braun et

al., 2020; Koelbl, 2020; Carstens and Freybote, 2021; Paulus et al., 2025). Despite this, the specific role of ESG-related sentiment within REIT disclosures remains largely unexplored.

For non-REITs, however, ESG-specific sentiment is clearly priced. Positive ESG-news sentiment lowers stock-price crash risk, especially when traditional disclosure and analyst coverage are weak, and ESG news sentiment generates abnormal returns, with negative ESG news having a stronger effect than positive news (Yu et al., 2023; Dorfleitner and Zhang, 2024; Jeong et al., 2025). Likewise, the tone of ESG-related language in 10-K filings significantly affects stock returns around disclosure dates, indicating that investors do not treat ESG language and ESG-related news as background noise but actively trade on these sentiment signals (Ignatov, 2023). Therefore, we address this gap in the REIT context by analyzing the effect of ESG-related sentiment in REIT 10-K and 10-Q filings as well as standalone sustainability reports as supported and recommended by the NAREIT (NAREIT, 2025b). Our first hypothesis is:

H1: ESG-related sentiment in REIT corporate disclosure is associated with CARs of US-REITs.

3.3.3 A disaggregated view of the ESG impact

The overall assessment of ESG has led to divergent results in past studies, partly because ESG combines dimensions with differing financial relevance. Recent work therefore emphasizes a pillar- or component-level perspective to understand ESG impacts (Erol et al., 2023; Fan et al., 2024; Zheng and Lee, 2026; Han et al., 2025). For the environmental pillar, evidence is mixed. Environmental initiatives such as certifications and emissions reductions can support lower financing costs and, in the REIT context, "greenness" is associated with stronger operating performance, but environmental efforts can also be costly and are not guaranteed to translate into higher profitability or returns (Bauer and Hann, 2010; Morri et al., 2021, 2024; Brounen and Marcato, 2018; Fan et al., 2024). In broader corporate-finance samples, higher environmental- and social-risk scores may reduce corporates' financial stability and raise their default risks incurring default costs (Cohen, 2022).

Besides the "E", social performance emerges as the most consistently positive driver of financial outcomes in the context of ESG. Firms disclosing strong social metrics partly outperform peers, earn valuation premia and improved investor sentiment, and long-horizon institutions systematically underweight stocks with negative E and S flags (Brounen and Marcato, 2018; Nofsinger et al., 2019; Carnini Pulino et al., 2022). In REITs,

social performance is positively associated with future returns firm performance and has a robust influence on performance in meta-analytic evidence, with E-investing and especially S-investing practices identified as the main financial performance drivers (Erol et al., 2023; Fan et al., 2024; Zheng and Lee, 2026). The governance pillar generally shows the most nuanced and context-dependent patterns. In non-REIT samples, there is a positive relationship between governance and corporate profitability, however only observed in firms with weak governance (Kim and Li, 2021). In early REIT studies, governance was found to matter to capital market participants (Kohl and Schäfers, 2012), while now governance scores are often insignificant as stand-alone performance predictors and can even be associated with adverse outcomes (Brounen and Marcato, 2018; Erol et al., 2023; Morri et al., 2024; Zheng and Lee, 2026).

The evidence in sentiment analysis shows that overall ESG news sentiment is positively related to corporate performance (driven by social and governance news sentiment), whereas environmental news sentiment is insignificant (Han et al., 2025). These findings support the notion that both the strength and direction of ESG relationships are shaped by disaggregating ESG into its components. In both performance and sentiment studies, social and environmental metrics tend to show the clearest economic effects, whereas governance often behaves more as a conditioning or moderating factor than a primary return driver, especially in REITs (Erol et al., 2023; Fan et al., 2024; Morri et al., 2021, 2024; Zheng and Lee, 2026). This motivates our second hypothesis:

H2: Sentiment regarding individual ESG pillars holds more explanatory power towards REIT returns than aggregate ESG sentiment.

3.3.4 Heterogeneity of ESG sentiment in REIT sub-sectors

Different real estate sectors serve different user groups and have distinct operational and technological profiles, so aggregating them can easily obscure heterogeneous ESG effects. Prior work shows that the information content of disclosure tone is property-type specific. Forward-looking tone in REIT financial statements predicts subsequent returns for residential and retail REITs, behaves differently for office REITs, and carries no informative value for industrial REITs, indicating that investors interpret similar linguistic signals differently across asset classes (Carstens and Freybote, 2021). Liang et al. (2021) likewise document that also ESG performance varies systematically with REIT portfolio focus. REITs that concentrate on less transparent, service-intensive assets such as hotels and hospitals tend to exhibit weaker environmental and social responsibility scores and lower overall ESG performance, while commercial offices and parts of the residential and industrial stock

are more transparent on environmental performance because they are more often subject to professional environmental assessment schemes and regulatory frameworks. Governance scores show no systematic differences across asset types, consistent with governance being largely determined by the common REIT regulatory and corporate-law framework rather than by the specific underlying assets (Liang et al., 2021). Additionally, Jeong et al. (2025) find that ESG news sentiment has the strongest positive association with performance in industries with pronounced ESG concerns and that social and governance news sentiment dominate these effects, suggesting that investors selectively amplify the ESG dimensions that are most material for a given sector.

Taken together, these findings imply that the three ESG pillars are unlikely to be uniformly priced across REIT sub-sectors. From an investor viewpoint, environmental sentiment should be most relevant where carbon and energy risks dominate and signal future retrofit and capex needs (e.g. residential, office, industrial, lodging, health care, data centers), social sentiment where human-service intensity and direct stakeholder contact are highest (e.g. lodging, health care, retail), and governance mainly as a background condition under a common REIT regime that becomes critical primarily in cases of visible governance weaknesses. This leads to our third and last hypothesis:

H3: ESG-related sentiment in REIT corporate disclosures has varying impacts across REIT sub-sectors.

3.4 Data and Methodology

The primary data we investigate contains the textual data from yearly and quarterly financial statements mandated by the SEC (10-K, 10-Q filings) for publicly traded U.S. equity REITs and hand-collected standalone ESG, sustainability, and Corporate Social Responsibility (CSR) reports (summarized as ESG reports) as well as financial data for each individual REIT. Additionally, we utilize macroeconomic and market-specific metrics to control for the current economic environment. For our analysis, we consider the data of 174 REITs that were NAREIT index constituents at any time between 2016 and 2025. This period is selected due to the limited availability of ESG reports before 2016 where the relevance of ESG-related reporting was comparably low to today. In total we have gathered ~ 1,500 Form 10-K, ~ 3,600 Form 10-Q and ~ 400 ESG reports.

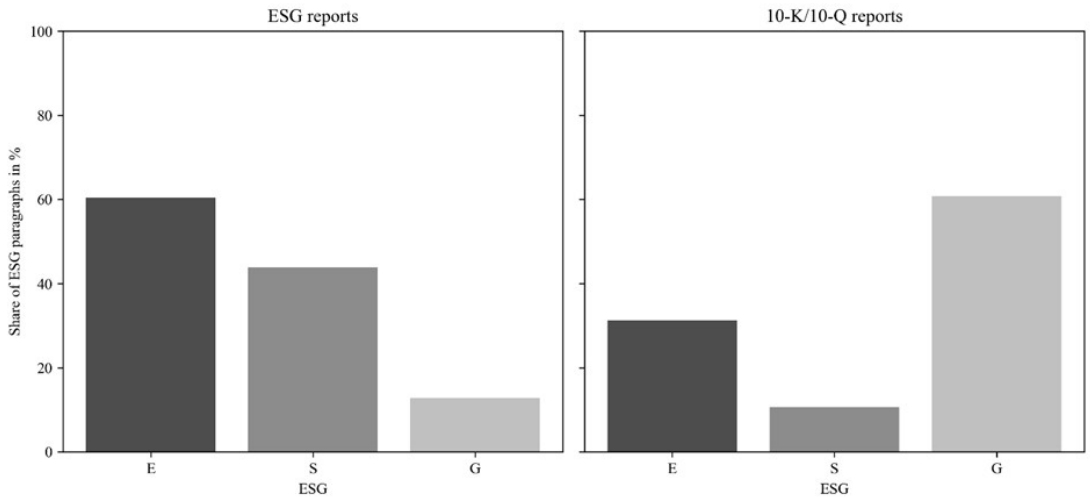
3.4.1 Filtering for ESG Relevance

To classify the derived text into the three pillars E, S, and G, we utilize a task-specifically fine-tuned ‘Robustly Optimized BERT Pretraining Approach’ (RoBERTa) model. RoBERTa is

originally developed by Liu et al. (2019) and based on the 'Bidirectional Encoder Representations from Transformers' (BERT) model introduced by Devlin et al. (2019). By using extensively pretrained models, we are minimizing the need for a training dataset, as the learning process of the overall textual understanding has already happened. Therefore, it is only necessary to fine-tune the models for the desired task. For fine-tuning, we utilize the *environmental_2k, social_2k,* and *governance_2k* dataset made available on Huggingface by Schimanski et al. (2024). These datasets each consist of approximately 2,000 sentences regarding their specific ESG pillar. The resulting ESG-RoBERTa is then used for a multiclass classification task where each paragraph is labelled regarding its affiliation with the three individual parts of ESG. Also a multiple or no classification (labeled as neutral) of the paragraphs is possible.

Figure 3.1 below shows the number of paragraphs classified as E, S, and G for both the ESG reports and 10-K filings. Across both disclosure types, E-related sections account for a larger share of ESG-specific text than S-related sections. In ESG reports, G-related segments make up the smallest share, whereas in mandatory SEC filings they represent the largest share. This pattern is plausible since standalone ESG reports are an additional, largely voluntary channel in which firms mainly highlight environmental and social initiatives (NAREIT, 2025b), while 10-K and 10-Q filings are tightly regulated documents whose core content (board structure, risk factors, controls, legal matters, financial policies) is inherently governance-oriented, resulting in a much higher proportion of G-related language.

Figure 3.1 Number of ESG Segments in the ESG Reports and Form 10-K/10-Q Reports



3.4.2 Derivation of Tone Measures

For the task of sentiment classification, we again utilize the RoBERTa model. This time, we fine-tune the model using the 'Finance Phrase-bank' dataset by Malo et al. (2014). This dataset consists of ~ 4,800 messages from a financial context that are each prelabeled as "negative", "neutral" or "positive" sentiment. With the resulting fine-tuned Sentiment-RoBERTa model, we classify each paragraph into one of the three sentiment classes.

After classifying the tone of each paragraph in the Form 10-K and 10-Q filings as well as the ESG reports, we aggregate these labels to construct the Net Positive Tone (*NPT*) for each document. The *NPT* reflects the relative predominance of positive paragraphs by comparing the net number of positive paragraphs (i.e., positive minus negative) to the total number of paragraphs, as shown in Equation 3.1:

$$NPT_t = \frac{(\sum_1^I positive\ paragraphs_{i,t} - \sum_1^I negative\ paragraphs_{i,t})}{(\sum_1^I total\ paragraphs_{i,t})} \tag{3.1}$$

where *i* denotes the number of paragraphs of a financial report and *t* denotes the year the report was published. *NPT* ranges from -1 to 1, where values below 0 indicate a tendency toward a generally negative tone, and values above 0 indicate a tendency toward a more positive overall tone.

3.4.3 Event Study and Regression analysis

For our regression analysis, we employ an event study methodology based on an Ordinary Least Squares (OLS) regression framework. The dependent variable is the CAR for each firm around the publication dates of the reports. For the 10-K and 10-Q filings, we use the EDGAR timestamps specified in the disclosures, while for ESG reports, we use the publication dates indicated in press releases on the companies' websites. The CARs are calculated using the historical mean-adjusted return model, which assumes that a firm's normal return can be approximated by its average return over an estimation window. We define the estimation window as the period from [–120, –30] trading days before the event to avoid any influence from the event itself. We consider four event windows [–1,1], [–3,3], [–5,5] and [–1,10] capturing short-, medium-, and longer-term market reactions around the event (Koelbl, 2020). To ensure robust statistical inference, we use two-way clustered standard errors to account for both serial correlation within firms and cross-sectional correlation across firms at specific points in time. This adjustment mitigates potential biases arising from contemporaneous market shocks. The abnormal return for firm i on day t is given by:

$$AR_{i,t} = R_{i,t} - \bar{R}_i \tag{3.2}$$

where $R_{(i,t)}$ denotes the actual return of firm *i* on day *t*, and $\bar{R}_i$ is the average return of the same firm over the estimation window. The CARs are then calculated by summing the abnormal returns over the event window:

$$CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} AR_{i,t} \tag{3.3}$$

To analyze the relationship between sentiment and market reactions, we regress the CARs on the *NPT* of the reports and include a set of control variables The general regression specification is:

$$CAR_i = \beta_0 + \beta_1 NPT_i + \beta_2 X_{i,t} + \varepsilon_i \tag{3.4}$$

where CAR_i is the cumulative abnormal return for firm i during the event window, NPT_i denotes the tone of the disclosure, $X_{i,t}$ represents the different control variables and ϵi is the error term.

We use a range of macroeconomic, market-based, and firm-level control variables. Macroeconomic conditions are captured by quarterly U.S. gross domestic product (*GDP*) growth, measured as the lagged change in log *GDP*, and by the monthly unemployment rate (*UNRATE*), included as a rolling standardized z-score at t–1. Market conditions are reflected by the lagged daily change in the S&P 500 (*SP500*) log return in lag(1), the lagged daily change in the effective federal funds rate (*DFF*), the lagged monthly change in the Moody's seasoned Baa–Aaa corporate bond yield spread (*SPREAD*), the lagged standardized z-score of the news-based economic policy uncertainty index (*UNC*) (Baker et al., 2016), and the lagged standardized GDELT[1] z-score at t–1 (*GDELT*) (Leetaru and Schrodt, 2025). Firm-level characteristics are controlled for using lagged quarterly leverage (*LEVERAGE*), lagged log market capitalization (*MCAP*), and the lagged log market-to-book ratio (*MTB*). All variables are transformed and standardized exactly as reported in Table 3.1, which also provides their descriptive statistics.

Overall, daily *SP500* returns and changes in the federal funds rate are close to zero with moderate volatility, consistent with typical short-term market dynamics. The standardized *GDELT, UNRATE,* and *UNC* measures are close to zero on average, but exhibit pronounced tails, indicating periods of heightened news sentiment, labor-market stress, and macro

[1] The GDELT project is a global, real-time news analytics database that monitors media from nearly every country and language, quantifying events and sentiment across political, economic, environmental, social, and governance domains and dynamics.

uncertainty. *GDP* growth and *SPREAD* vary less, reflecting smoother macroeconomic movements relative to financial conditions. At the firm level, REITs display moderately similar leverage, some dispersion in size (*MCAP*), and substantial heterogeneity in valuations (*MTB*). Finally, we also consider time-fixed effects to absorb major macroeconomic shock phases such as the COVID-19 pandemic, the start of the invasion of Ukraine, and the interest rate hike cycle, thereby capturing general changes in investor behavior that are not related to company-level disclosures.

Table 3.1 Descriptive Statistics

Variable	Transformation	Count	Mean	Median	Std	Min	Max
NPT	none	4,552	-0.015	-0.010	0.033	-1.000	0.083
NPTt-1	none	4,051	-0.014	-0.011	0.021	-0.270	0.037
SP500	lΔln(SP500)	3,648	0.000	0.000	0.013	-0.165	0.130
DFF	Δ(DFF)	3,648	0.001	0.000	0.040	-0.850	0.750
GDELT	z-score	3,590	-0.029	-0.005	1.062	-8.248	6.797
GDP	Δln(GDP)	3,593	0.004	0.000	0.014	-0.086	0.084
UNRATE	z-score	3,471	0.122	-0.772	4.867	-3.065	48.719
SPREAD	Δ(SPREAD)	3,593	-0.007	-0.010	0.085	-0.250	0.440
UNC	z-score of ln(1+UNC)	3,471	0.215	0.184	1.488	-3.275	7.550
LEVERAGE	none	331,554	0.503	0.480	0.176	0.000	1.482
MCAP	ln(MCAP)	350,225	21.895	21.934	1.969	14.169	35.318
MTB	ln(MTB)	326,209	0.629	0.581	1.392	-4.921	16.736

Note: The table presents descriptive statistics for the sample period 2016–2025. NPT is the aggregated sentiment score based on RoBERTa sentiment classifications and is computed at the report-date level. NPT_{t-1} is the lagged sentiment measure (constructed using the previous-year average by REIT). SP500 is the one-day lag of the S&P 500 log return (Δln), DFF is the one-day lag of the change in the effective federal funds rate, and GDELT is the standardized GDELT measure. GDP is the month-to-month change in log GDP shifted by one month, UNRATE is the standardized unemployment rate, SPREAD is the month-to-month change in the Moody's Baa–Aaa corporate bond yield spread shifted by one month, and UNC is the standardized ln(1+UNC) political uncertainty measure. LEVERAGE, MCAP, and MTB enter the regressions as one-period lagged firm controls. MCAP and MTB are expressed in logs.

3.5 Results

Table 3.2 shows the results for the 10-K, 10-Q and ESG reports on an overall and joint ESG level. The findings suggest that the publication of official disclosure mandatory by the SEC is associated with positive and significant mean CARs in the majority of the event windows ([-1,1]; [-3,3]; [-5,5]). This suggests that investors acknowledge the informational value of corporate disclosure and the managerial sentiment within those reports. This pattern is consistent with the established literature documenting that annual reports reduce information asymmetry and uncertainty and contain investor-relevant qualitative signals (Doran et al., 2012; Koelbl, 2020; Carstens and Freybote, 2021). The sentiment in voluntary ESG reports on the other hand is not significant. Also, neither the aggregate ESG sentiment in 10-K/10-Q filings nor the sentiment in voluntary reports shows a clear overall association with the CARs. A potential interpretation is that investors treat the publication of core financial filings itself and the underlying managerial sentiment as a value-relevant event,

while high-level ESG language, especially when reported outside the regulated financial statements, appears too noisy at the aggregate level to shift prices. Another explanation could be that separate ESG reporting might feel like "green-washing" or a sign of over-investing in ESG matters by the companies to the investors. We therefore reject our H1, which stated that ESG-related sentiment in REIT corporate disclosure is associated with the CARs. This rejection again motivates the subsequent disaggregated analysis by ESG pillar and sub-sector.

Table 3.2 Regression Results on the Overall Disclosure and Overall ESG Sentiment

	10-K/10-Q vs. ESG reports							
	[-1,1]	**[-3,3]**	**[-5,5]**	**[-1,10]**	**[-1,1]**	**[-3,3]**	**[-5,5]**	**[-1,10]**
	Overall - 10-K/10-Q				**Overall - ESG Reports**			
NPT	0.0733*	0.1192**	0.1679**	0.1424	0.0036	-0.1169	-0.0705	-0.0295
NPT_{t-1}	0.0886	0.0630	0.1581	0.0173	-0.0194	0.0069	-0.2015	-0.0649
SP500	0.4582***	0.9327***	0.8166***	0.9531***	0.9175**	1.0789*	1.0219	1.2462**
DFF	0.0084	-0.0053	0.0600	0.0725*	-0.0325	-0.0219	-0.1163**	-0.0148
GDELT	0.0013	0.0022	0.0004	-0.0033	-0.0005	0.0019	-0.0013	-0.0031
GDP	0.4125***	0.6651***	0.7626***	0.3490*	1.1218*	2.3987***	2.1013**	2.6361***
UNRATE	0.0002	-0.0001	-0.0002	-0.0020**	0.0006	-0.0005	-0.0024	-0.0020
SPREAD	0.0448*	0.0355	0.0976*	0.2088***	0.0763	0.2088**	0.2160	0.2890**
UNC	-0.0021	-0.0066**	-0.0083**	-0.0124***	0.0006	-0.0004	0.0017	0.0008
LEVERAGE	0.0039	0.0183	0.0279	-0.0078	0.0379	-0.1900	-0.2502	-0.1889
MCAP	-0.2557**	-0.3825***	-0.3336*	-0.4719	0.0178	-0.0756	-0.1035	-0.0694
MTB	-0.0029	-0.0085*	-0.0114*	-0.0197***	-0.0398*	-0.0094	0.0093	-0.0298
R^2 Within	0.0494	0.0944	0.0710	0.1054	0.2112	0.3129	0.2513	0.3385
	ESG - 10-K/10-Q				**ESG - ESG Reports**			
NPT	-0.0191	0.0275	0.0315	0.0444	0.0305	-0.0652	-0.0296	0.0537
NPT_{t-1}	-0.0478**	-0.0351	-0.0560	-0.1009***	-0.0517	-0.0344	-0.2428**	-0.0824
SP500	0.4560***	0.9342***	0.8213***	0.9454***	0.9268***	1.0911**	0.9956	1.2953**
DFF	0.0103	-0.0022	0.0652	0.0761*	-0.0313	-0.0216	-0.1198**	-0.0050
GDELT	0.0014	0.0022	0.0003	-0.0034	-0.0008	0.0015	-0.0021	-0.0033
GDP	0.4342***	0.6947***	0.7768***	0.3672*	1.1233**	2.4126***	1.9817**	2.6243***
UNRATE	0.0001	-0.0002	-0.0003	-0.0021**	0.0007	-0.0004	-0.0021	-0.0018
SPREAD	0.0531*	0.0458	0.1058*	0.2177***	0.0808	0.2104**	0.2173	0.2908**
UNC	-0.0021	-0.0068**	-0.0084**	-0.0126***	0.0007	-0.0002	0.0012	0.0005
LEVERAGE	0.0036	0.0177	0.0233	-0.0097	0.0492	-0.1808	-0.2134	-0.1621
MCAP	-0.2568**	-0.3724***	-0.3152*	-0.4537	0.0159	-0.0766	-0.1118	-0.0665
MTB	-0.0031	-0.0090*	-0.0137**	-0.0212***	-0.0376*	-0.0077	0.0205	-0.0308
R^2 Within	0.0486	0.0938	0.0689	0.1052	0.2187	0.3092	0.2676	0.3414

Note: The table reports panel OLS estimates of cumulative abnormal returns (CAR) over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings and ESG reports on the overall and overall ESG level.. NPT is the sentiment measure; NPT_{t-1} is its one-year lag. SP500 is the lagged S&P 500 return, DFF is the change in the effective federal funds rate, and GDELT is the GDELT-based news measure. GDP denotes the (lagged) growth rate of U.S. gross domestic product, UNRATE is the U.S. unemployment rate, and SPREAD is the Moody's Baa–Aaa corporate bond yield spread. UNC is the political uncertainty index. LEVERAGE is the firm leverage control, MCAP is (log) market capitalization, and MTB is (log) market-to-book. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R^2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3.3 reports the pillar-level results for both SEC filings and ESG reports. For annual and quarterly filings, pillar-level ESG sentiment is significantly associated with positive CARs for the environmental and social pillars, while governance sentiment remains insignificant,

in line with prior evidence on the limited standalone impact of G (Zheng and Lee, 2026). Environmental sentiment emerges as the most stable driver, showing a positive and robust relationship with REIT returns across three event windows ([-3,3], [-5,5], [-1,10]) whereas social sentiment is weaker and only marginally significant in the [-1,10] window. In the more granular analysis of ESG reports, we similarly find no significant effects for governance-related language, but in this case environmental sentiment is also insignificant, while the social pillar is associated with negative CARs in the [-3,3] window. Given that ESG reports are typically framed as CSR or sustainability reports and place strong emphasis on environmental and especially social themes, the social component likely dominates the aggregate sentiment signal in this disclosure channel. The weak or even adverse market reaction to social sentiment in voluntary ESG reports is consistent with the notion that social initiatives are harder to link to immediate, measurable financial outcomes for REITs, and that investors may discount generic or promotional S-language when it is not clearly tied to cash-flow-relevant fundamentals (Carnini Pulino et al., 2022).

Table 3.3 Regression Results on the Pillar-Level ESG Sentiment

	10-K/10-Q vs. ESG reports							
	[-1,1]	**[-3,3]**	**[-5,5]**	**[-1,10]**	**[-1,1]**	**[-3,3]**	**[-5,5]**	**[-1,10]**
	Environmental - 10-K/10-Q				**Environmental - ESG Reports**			
NPT	0.0083	0.0227**	0.0232*	0.0214*	0.0046	0.0020	-0.0060	0.0544
NPT_{t-1}	-0.0092	-0.0132	-0.0132	-0.0210	-0.0577	-0.0820	-0.2054***	-0.0608
SP500	0.4833***	0.9339***	0.8088***	0.9646***	0.8883**	1.1142**	0.9863	1.2710**
DFF	0.0135	-0.0050	0.0684	0.0778*	-0.0443	-0.0271	-0.1439**	-0.0060
GDELT	0.0011	0.0020	-0.0003	-0.0043	-0.0011	0.0008	-0.0026	-0.0035
GDP	0.4322***	0.6411***	0.7544***	0.4112**	1.0900*	2.4100**	1.9053**	2.5898***
UNRATE	0.0002	-0.0001	-0.0003	-0.0017	0.0006	-0.0004	-0.0022	-0.0018
SPREAD	0.0497*	0.0446	0.1157**	0.2093***	0.0812	0.2175**	0.2129	0.2894**
UNC	-0.0028	-0.0081**	-0.0095**	-0.0138***	0.0008	-0.0002	0.0009	0.0004
LEV	0.0051	0.0126	0.0370	0.0086	0.0482	-0.1559	-0.1941	-0.1673
MCAP	-0.2566**	-0.3579**	-0.2375	-0.3709	0.0158	-0.0725	-0.0966	-0.0582
MTB	-0.0022	-0.0087	-0.0157**	-0.0213***	-0.0381*	-0.0119	0.0045	-0.0378
R^2 Within	0.0459	0.0901	0.0662	0.0968	0.2266	0.3170	0.2820	0.3438
	Social - 10-K/10-Q				**Social - ESG Reports**			
NPT	0.0077	0.0208	0.0195	0.0264*	-0.0176	-0.1517*	-0.0625	0.0234
NPT_{t-1}	0.0179	-0.0005	0.0302	0.0265	0.0439	0.0890	-0.0366	-0.0518
SP500	0.5456***	1.1410***	0.9897***	1.1623***	0.8836**	0.9902*	0.9961	1.2974**
DFF	0.0176	0.0016	0.0869	0.0898*	-0.0350	-0.0259	-0.1020**	-0.0035
GDELT	0.0014	0.0044	0.0013	-0.0039	0.0000	0.0029	-0.0003	-0.0032
GDP	0.3257***	0.5207***	0.5993***	0.3571*	0.8951	2.1014**	1.7453*	2.6931***
UNRATE	0.0008	-0.0002	-0.0002	-0.0008	0.0009	-0.0003	-0.0018	-0.0019
SPREAD	0.0371	0.0372	0.1053*	0.2217***	0.0464	0.1682	0.1704	0.2951*
UNC	-0.0032	-0.0102***	-0.0121***	-0.0158***	0.0003	-0.0009	0.0005	0.0005
LEV	0.0203	0.0386	0.0786	0.0534	0.0355	-0.2379	-0.2679	-0.1762
MCAP	-0.1814	-0.2930*	-0.0977	-0.0879	0.0249	-0.0587	-0.0872	-0.0680
MTB	-0.0043	-0.0165**	-0.0208*	-0.0290**	-0.0453**	-0.0241	-0.0029	-0.0303
R^2 Within	0.0437	0.1048	0.0709	0.0997	0.2129	0.3232	0.2163	0.3332
	Governance - 10-K/10-Q				**Governance - ESG Reports**			
NPT	-0.0424	-0.0291	-0.0275	-0.0330	0.0271	0.0306	0.0275	-0.0242
NPT_{t-1}	-0.0262	0.0060	0.0032	-0.0204	-0.0383	0.0099	-0.0340	-0.0871
SP500	0.4498***	0.9342***	0.8221***	0.9462***	0.8837**	1.1688**	1.0942	1.1401
DFF	0.0099	-0.0026	0.0650	0.0763*	-0.0405	-0.0059	-0.0960*	-0.0193
GDELT	0.0012	0.0021	0.0001	-0.0036	-0.0021	0.0008	0.0004	-0.0063
GDP	0.4259***	0.6959***	0.7804***	0.3825*	1.0081*	2.3325**	1.6553*	2.7183***
UNRATE	0.0001	-0.0002	-0.0003	-0.0021**	0.0008	-0.0000	-0.0017	-0.0025
SPREAD	0.0494*	0.0465	0.1072*	0.2192***	0.0574	0.1837	0.1650	0.3055*
UNC	-0.0022	-0.0069**	-0.0085**	-0.0127***	0.0008	-0.0004	0.0004	0.0009
LEV	0.0061	0.0213	0.0280	-0.0023	0.0023	-0.1921	-0.2560	-0.2187
MCAP	-0.2685**	-0.3953***	-0.3123*	-0.4204	0.0177	-0.0668	-0.0790	-0.0629
MTB	-0.0038	-0.0090	-0.0141**	-0.0228***	-0.0392**	-0.0148	-0.0087	-0.0325
R^2 Within	0.0503	0.0950	0.0689	0.1039	0.2329	0.2890	0.2035	0.3396

Note: The table reports panel OLS estimates of cumulative abnormal returns (CAR) over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings and ESG reports on the pillar level. NPT is the sentiment measure; NPT_{t-1} is its one-year lag. SP500 is the lagged S&P 500 return, DFF is the change in the effective federal funds rate, and GDELT is the GDELT-based news measure. GDP denotes the (lagged) growth rate of U.S. gross domestic product, UNRATE is the U.S. unemployment rate, and SPREAD is the Moody's Baa–Aaa corporate bond yield spread. UNC is the political uncertainty index. LEVERAGE is the firm leverage control, MCAP is (log) market capitalization, and MTB is (log) market-to-book. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R^2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Since ESG reporting is not mandated by NAREIT, the availability of sustainability reports varies across REITs. While the sample is sufficient to analyze sentiment separately for the individual pillars, it does not allow for reliable pillar-level comparisons across asset classes. In contrast, 10-K and 10-Q filings are available for all REITs and therefore support both granular analysis and subsequent sector-level differentiation. Tables 3.4 - 3.6 report the corresponding OLS regression results for the different ESG pillars at the property-type level (industrial, residential, lodging, health care, office, retail, data center, other). The coefficients differ meaningfully in both sign and magnitude, consistent with earlier evidence that tone and ESG and REIT performance in general vary by property type (Carstens and Freybote, 2021; Liang et al., 2021). Environmental sentiment shows a relatively stable and positive association with CARs, with significant effects for several operationally intensive asset classes (industrial, lodging, health care), which is consistent with economic intuition: environmental factors directly affect building performance, operating expenses, and compliance risks. Investors may therefore interpret more positive environmental disclosures as indicative of lower physical or regulatory exposure, particularly when property assets are operationally intensive. Social sentiment also yields positive results in two sectors (lodging, other), although less consistently, which aligns with the limited immediate monetization of social initiatives in real estate valuations. As the measurement of social attributes improves in the overall real estate sector (e.g. tenant well-being indicators, employee-related disclosures), the relevance of S may increase over time. Governance sentiment remains insignificant except for residential and retail REITs. The lack of significance and mixed results in the other sub-sectors (Kim and Li, 2021; Morri et al., 2024; Zheng and Lee, 2026) are likely due to governance-related risks already being mitigated through REIT-specific regulatory structures, which limits the incremental information contained in narrative governance language.

Overall, the environmental and social pillars of ESG sentiment appear to be more relevant for investors. This is in line with the literature finding that E and S dominate ESG results (Nofsinger et al., 2019; Brounen and Marcato, 2018; Fan et al., 2024) and that they are the most consistent positive drivers (Brounen and Marcato, 2018; Carnini Pulino et al., 2022; Erol et al., 2023; Zheng and Lee, 2026). It supports the argument that aggregated ESG measures obscure critical differences across E, S, and G components and confirms H2, indicating that investors process ESG information in a highly differentiated manner rather than responding to a unified "ESG signal" (Zheng and Lee, 2026).

Table 3.4 Regression Results on the Environmental and Sector-Level Sentiment

10-K/10-Q reports - Environmental								
	[-1,1]	[-3,3]	[-5,5]	[-1,10]	[-1,1]	[-3,3]	[-5,5]	[-1,10]
	Industrial				**Residential**			
NPT	0.0138	0.0210	0.0114	0.0467*	0.0014	0.0147	0.0150	0.0010
NPT_{t-1}	-0.0091	0.0337	0.0116	-0.0146	0.0070	-0.0038	-0.0184	0.0012
SP500	0.4136	0.7499	0.6885	0.2471	0.2818***	0.3086**	0.4014**	0.3009
DFF	0.1216***	0.1696***	0.1750***	0.0804**	0.0176	0.0388	0.1024*	0.1301**
GDELT	-0.0019	-0.0063	-0.0050	-0.0107***	0.0006	-0.0013	-0.0051**	-0.0027
GDP	-0.1795	-0.4740	-0.3149	-0.6268	-0.0925	0.0954	0.3832	-0.0125
UNRATE	0.0001	0.0020**	0.0022*	0.0001	0.0001	0.0005	0.0009	-0.0001
SPREAD	-0.0555	-0.1597***	-0.0945	-0.1055	0.0212	-0.0186	-0.0048	0.0448
UNC	-0.0002	0.0014	-0.0050	-0.0164*	0.0016	0.0025	0.0001	-0.0029
LEV	-0.1218**	-0.1740***	-0.1856***	-0.3530***	0.0120	0.0048	-0.0576	-0.0463
MCAP	-0.8294***	-1.4885***	-1.0834***	-1.6947***	-0.2489	-0.3600	-0.9621***	-2.3237***
MTB	-0.0042	-0.0021	-0.0089	-0.0152	-0.0297***	-0.0317**	-0.0289**	-0.0465**
R^2 Within	0.1636	0.2414	0.1719	0.3008	0.1112	0.1083	0.1500	0.2125
	Lodging				**Health Care**			
NPT	0.0264	0.0995*	0.0917*	0.0610	0.0155	0.0295*	0.0427*	0.0234
NPT_{t-1}	0.0317	0.0200	0.0287	0.0350	-0.0908*	-0.1019	-0.0860	-0.0803
SP500	1.4767**	2.5905***	1.3511	2.1111***	0.3822**	0.6933***	0.8037**	1.1693**
DFF	-0.0198	0.0210	-0.0038	-0.0446	0.0316	0.0024	0.0860	0.0880
GDELT	0.0124	0.0089	0.0113	0.0097	-0.0034	0.0004	-0.0036	-0.0082*
GDP	1.5753***	1.7331***	2.1722***	1.3556***	0.1777	0.1909	0.2338	0.1866
UNRATE	-0.0059	-0.0369***	-0.0133	0.0374***	-0.0046	-0.0172***	-0.0218***	-0.0077
SPREAD	0.2266**	0.4498***	0.6790***	0.5759***	0.0212	-0.0302	0.0204	0.2630**
UNC	-0.0129	-0.0208**	-0.0215**	-0.0283***	-0.0033	-0.0067	-0.0071	-0.0161***
LEV	0.2246*	0.3381***	0.3602*	0.3435	-0.2117**	-0.2477	-0.2483	-0.2311**
MCAP	-0.1134	0.1799***	0.1712	0.2060	-1.1828*	-2.6320**	-3.3240**	-2.9832***
MTB	0.0094	-0.0412***	0.0015	-0.0053	0.0176**	0.0216	0.0268	0.0200**
R^2 Within	0.1438	0.3208	0.1720	0.2379	0.1376	0.2372	0.2364	0.2661
	Office				**Retail**			
NPT	0.0172	0.0180	0.0602	0.0501	0.0101	0.0159	0.0280	0.0241
NPT_{t-1}	-0.0137	0.0036	-0.0621	-0.0391	-0.0032	-0.0044	0.0052	-0.0067
SP500	0.5236***	0.9995***	1.0997**	1.5820***	0.1832	0.7323**	0.6173**	0.9797***
DFF	0.0269	-0.0082	0.1152	0.1295	0.0112	0.0061	0.0698**	0.0617
GDELT	-0.0002	0.0024	-0.0009	-0.0050*	0.0019	0.0042	0.0047	0.0015
GDP	0.5877***	0.9044***	1.3619***	1.1447**	0.3211*	0.6177***	0.6441***	0.3775
UNRATE	0.0001	0.0008	0.0008	-0.0034***	0.0029**	0.0012	0.0001	-0.0022
SPREAD	0.0619*	0.0097	0.0236	0.1474*	-0.0031	0.0106	0.0784	0.2799**
UNC	0.0024	-0.0025	-0.0044	-0.0097*	-0.0032	-0.0094**	-0.0117***	-0.0213***
LEV	0.0404	-0.0608	-0.1267	-0.2507	0.1290	0.1378	0.2460	0.2157
MCAP	0.6953***	1.1035*	1.8556	2.3237	-0.6763	-0.6694	-0.8747	-1.6159**
MTB	-0.0272**	-0.0348**	-0.0455	-0.0964***	-0.0038	-0.0182	-0.0343**	-0.0074
R^2 Within	0.1289	0.1823	0.1821	0.1881	0.0860	0.1414	0.1399	0.1713
	Data Center				**Other**			
NPT	-0.1272***	-0.1083***	-0.0849	-0.1006***	-0.0090	-0.0043	-0.0284	-0.0091
NPT_{t-1}	-0.3276***	-0.3315***	-0.3653	-0.3790	-0.0058	0.0195	-0.0070	-0.0958*
SP500	0.6335***	1.0881***	1.0964	1.3867***	0.4607**	0.7689**	0.7654***	1.0626***
DFF	0.1231***	0.0978	0.2023***	0.2062***	-0.0204	-0.0522***	0.0255	0.0466*
GDELT	-0.0122***	-0.0151**	-0.0130**	-0.0130***	-0.0011	-0.0003	-0.0041	-0.0075**
GDP	0.0443	-0.2602	-0.1148***	-0.1659	0.4439**	0.7853***	0.6293**	0.4834**
UNRATE	0.0024***	-0.0015***	-0.0031	0.0084***	0.0003	0.0001	0.0001	-0.0004
SPREAD	-0.1283***	-0.1667***	-0.1148***	-0.2072***	0.0714	0.0974	0.1414	0.1955*
UNC	0.0052	0.0033	-0.0025	-0.0077	-0.0015	-0.0061**	-0.0085*	-0.0110**
LEV	-0.6690***	-0.6101	-0.8536***	-1.2468***	-0.0217	0.0595	0.0543	0.0259
MCAP	-6.3578***	-3.6945**	-3.7571***	-10.3842***	-0.3992*	-0.1297	-0.4444	-0.9095**
MTB	0.1279**	0.0827**	0.0339	0.2337***	0.0034	-0.0107	-0.0198	-0.0183
R^2 Within	0.6380	0.6030	0.4862	0.7028	0.0584	0.1030	0.1072	0.1508

Note: The table reports panel OLS estimates of CAR) over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings on the environmental level. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3.5 Regression Results on the Social and Sector-Level Sentiment

	10-K/10-Q reports - Social							
	[-1,1]	**[-3,3]**	**[-5,5]**	**[-1,10]**	**[-1,1]**	**[-3,3]**	**[-5,5]**	**[-1,10]**
	Industrial				**Residential**			
NPT	0.0090	-0.0075	-0.0206	-0.0073	-0.0132	-0.0082	0.0003	0.0057
NPT_{t-1}	-0.0946**	-0.1130***	-0.0330	-0.0585	-0.0000	-0.0108	-0.0031	0.0069
SP500	0.1815	0.1442	0.1673	0.0621	0.1879**	0.3083**	0.3492	0.1510
DFF	0.1179**	0.1284***	0.1587***	0.1210*	0.0485***	0.0817	0.1795	0.2311*
GDELT	-0.0048	-0.0080	-0.0087	-0.0168***	0.0004	0.0023	-0.0031	-0.0012
GDP	-0.7932*	-1.1721***	-1.1993**	-1.5042***	-0.1751	0.0797	0.3766*	-0.0529
UNRATE	0.0012*	0.0034**	0.0039**	0.0021	0.0006	0.0007	0.0012*	0.0005
SPREAD	-0.0973	-0.2180**	-0.1602	-0.2200**	-0.0031	-0.0293	-0.0164	0.0251
UNC	0.0018	0.0005	-0.0049	-0.0128***	0.0018	0.0012	-0.0024	-0.0043
LEV	-0.1384	-0.2355	-0.1680	-0.3080*	0.0183	0.0398	-0.0369	-0.0702
MCAP	-1.1700	-2.3574**	-1.5458*	-1.7147***	-0.3547	-0.6312*	-1.1951***	-3.1585***
MTB	0.0146	0.0156	0.0005	0.0160	-0.0283**	-0.0268*	-0.0238	-0.0446
R^2 Within	0.2781	0.3789	0.2935	0.3133	0.1432	0.1311	0.1722	0.2646
	Lodging				**Health Care**			
NPT	0.0541	0.1112**	0.0993**	0.1162***	0.0060	-0.0035	0.0094	0.0251
NPT_{t-1}	0.1318	0.0732	0.1753	0.1490	0.0000	-0.0042	0.0034	0.0152
SP500	1.1645*	2.8521***	1.6232	2.1245***	0.4219**	0.7926***	0.8073***	0.9761**
DFF	-0.1099	-0.0738	-0.1382	-0.1675	0.0242	-0.0079	0.1021	0.0997*
GDELT	0.0152	0.0126	0.0184	0.0164	-0.0032	0.0038	-0.0010	-0.0079
GDP	1.1807***	1.2891**	1.3388***	0.9420**	0.1862	0.0803	0.0716	0.1171
UNRATE	-0.0092	-0.0407***	-0.0180	0.0336***	-0.0040	-0.0170***	-0.0223***	-0.0061
SPREAD	0.2011**	0.4193***	0.6028***	0.5930***	-0.0236	-0.0714	-0.0032	0.2063**
UNC	-0.0122	-0.0186***	-0.0214**	-0.0303***	-0.0017	-0.0065	-0.0073*	-0.0150***
LEV	0.2567	0.5036***	0.6710***	0.5474**	-0.2118***	-0.2725*	-0.2734*	-0.2870**
MCAP	-0.3110	-0.0695	-0.1653	-0.1064	-1.4072**	-2.8641**	-3.4189***	-3.6071***
MTB	0.0121	-0.0318**	0.0130	0.0039	0.0154	0.0165	0.0251	0.0227
R^2 Within	0.1471	0.3438	0.2151	0.3046	0.1152	0.2287	0.2231	0.2750
	Office				**Retail**			
NPT	-0.0050	-0.0209	-0.0101	-0.0437	-0.0033	-0.0048	-0.0232	-0.0071
NPT_{t-1}	0.0025	0.0028	0.0240	0.0008	0.0102	0.0044	0.0154	0.0039
SP500	0.4426	1.0823*	1.5113*	2.2608**	0.2847	0.6888**	0.7679***	1.1930***
DFF	0.0491***	0.0264	0.2163***	0.2313	0.0030	0.0057	0.1025**	0.0596
GDELT	-0.0012	0.0030	-0.0020	-0.0066	0.0021	0.0023	0.0007	-0.0011
GDP	0.6580***	07696***	1.2197*	1.2629	0.2722	0.6609**	0.6664**	0.3359
UNRATE	0.0012**	0.0005	0.0003	-0.0037**	0.0028**	0.0013	-0.0001	-0.0025
SPREAD	0.0654	-0.0208	-0.0040	0.2001	-0.0022	0.0129	0.0786	0.3186**
UNC	0.0017	-0.0042	-0.0076	-0.0150*	-0.0033	-0.0083*	-0.0106*	-0.0243***
LEV	0.0053	-0.0526	-0.1790*	-0.3461	0.1665	0.1374	0.3297	0.2617
MCAP	0.8785**	1.6006**	2.9067	3.7295	-0.6521	-0.6187	-0.5620	-1.7144**
MTB	-0.0341*	-0.0494**	-0.0588	-0.1114**	-0.0094	-0.0294	-0.0582**	-0.0089
R^2 Within	0.1781	0.2172	0.2245	0.2431	0.0948	0.1465	0.1559	0.1880
	Data Center				**Other**			
NPT	-0.0929***	-0.0767***	-0.1317***	-0.0514***	0.0199*	0.0424***	0.0261	0.0210
NPT_{t-1}	0.0035	-0.0110	0.0639**	-0.0595***	0.0126	0.0169	0.0378	-0.0126
SP500	0.6663***	1.0485**	1.3494**	1.3883***	0.7211**	1.2669***	1.1062**	1.7027***
DFF	0.0969***	0.0846***	0.1831***	0.1587***	-0.0160	-0.0400	-0.0014	0.0699*
GDELT	-0.0100***	-0.0171**	-0.0104	-0.0100***	-0.0031	0.0013	-0.0012	-0.0082*
GDP	-0.3666	-0.6899***	-0.8099***	-0.6741***	0.3137*	0.7361***	0.5246**	0.4260**
UNRATE	-0.0033	-0.0059**	-0.0106	0.0044	0.0008	0.0006	0.0007	0.0007
SPREAD	-0.2326***	-0.2803***	-0.2967***	-0.3308***	0.0454	0.0513	0.0813	0.1523
UNC	0.0006	-0.0029***	-0.0074	-0.0119	0.0012	-0.0069	-0.0113	-0.0082*
LEV	-0.6961***	-0.4023***	-1.5983	-1.4663***	-0.0116	0.0825	0.0294	0.0824
MCAP	-11.8057***	-8.4912***	-10.2034***	-14.5506***	-0.2134	-0.0229	-0.6848	-0.8019
MTB	0.3170***	0.2623***	0.3576***	0.4219***	0.0065	-0.0146	-0.0184	-0.0300
R^2 Within	0.7561	0.7310	0.6144	0.7616	0.0916	0.1995	0.1753	0.2171

Note: The table reports panel OLS estimates of CAR over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings on the social level. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3.6 Regression Results on the Governance and Sector-Level Sentiment

	10-K/10-Q reports - Governance							
	[-1,1]	**[-3,3]**	**[-5,5]**	**[-1,10]**	**[-1,1]**	**[-3,3]**	**[-5,5]**	**[-1,10]**
	Industrial				**Residential**			
NPT	-0.0305	-0.0682	-0.0752	-0.0196	0.0205**	0.0449**	0.0826***	0.0411
NPT_{t-1}	0.0375	0.0632	0.0258	-0.0588	0.0113	0.0101	-0.0203	0.0105
SP500	0.4047	0.7140	0.6533	0.2428	0.2933***	0.4120***	0.5371***	0.4071**
DFF	0.1218***	0.1676***	0.1782***	0.0838**	0.0190	0.0539	0.1210**	0.1383**
GDELT	-0.0022	-0.0065	-0.0057	-0.0102**	0.0001	-0.0005	-0.0030	-0.0019
GDP	-0.1544	-0.4398	-0.2812	-0.5761	-0.1324	0.1308	0.4683*	0.0743
UNRATE	0.0001	0.0019**	0.0021*	-0.0000	-0.0003	0.0004	0.0008	-0.0015
SPREAD	-0.0524	-0.1525***	-0.0900	-0.0913	0.0201	-0.0139	0.0318	0.1019
UNC	0.0002	0.0019	-0.0038	-0.0149*	0.0028*	0.0039	0.0022	-0.0009
LEV	-0.1278**	-0.2143***	-0.1879***	-0.3548***	-0.0227	-0.0480	-0.1268*	-0.1733**
MCAP	-0.8518***	-1.6199***	-1.1538***	-1.6163***	-0.3149	-0.7521***	-1.3637***	-2.7022***
MTB	-0.0020	0.0058	-0.0010	-0.0114	-0.0187***	-0.0182***	-0.0101	-0.0276*
R^2 Within	0.1575	0.2490	0.1685	0.2762	0.1077	0.1085	0.1367	0.2250
	Lodging				**Health Care**			
NPT	-0.2651*	-0.1440	-0.1888	-0.1550	0.0049	0.0300	0.0302	-0.0199
NPT_{t-1}	-0.3009	-0.2214	-0.4941	-0.3592	-0.0202	-0.0066	0.0266	0.0800***
SP500	0.8624	2.3296***	1.3027	1.7207***	0.3490**	0.6362***	0.6848**	0.8757***
DFF	-0.0837	-0.0072	-0.0836	-0.0940	0.0066	-0.0369	0.0436	0.0648
GDELT	0.0106	0.0077	0.0109	0.0104	-0.0020	0.0006	-0.0026	-0.0067
GDP	1.3233***	1.7106***	1.9059***	1.1453**	0.2682	0.3140	0.3149	0.2718
UNRATE	-0.0091	-0.0376***	-0.0148	0.0281**	-0.0042	-0.0161***	-0.0204***	-0.0053
SPREAD	0.2410***	0.4446***	0.5670***	0.5787***	0.0104	-0.0283	0.0066	0.2423**
UNC	-0.0059	-0.0113*	-0.0131*	-0.0198***	-0.0027	-0.0062	-0.0070	-0.0143***
LEV	0.2815*	0.5397***	0.5249***	0.5053**	-0.1556***	-0.1624	-0.1720*	-0.2334**
MCAP	-0.1736	0.1513	-0.0080	0.1159	-1.1855*	-2.5577**	-2.9556***	-3.1543***
MTB	0.0025	-0.0419***	-0.0022	-0.0145	0.0143**	0.0216	0.0258	0.0218**
R^2 Within	0.1392	0.2947	0.1668	0.2501	0.1148	0.2102	0.2048	0.2585
	Office				**Retail**			
NPT	0.0293	0.0273	0.1031	0.1486	-0.0576*	-0.0845***	-0.0797	-0.0758
NPT_{t-1}	-0.0383	-0.0558	0.0409	-0.0414	-0.0509	-0.0358	-0.0352	-0.0678
SP500	0.5542***	0.9920***	1.0732**	1.5604***	0.1356	0.6498**	0.5601*	0.9020***
DFF	0.0267	-0.0072	0.1122	0.1289	0.0103	0.0003	0.0684*	0.0674*
GDELT	-0.0006	0.0022	-0.0015	-0.0055*	0.0015	0.0035	0.0040	0.0007
GDP	0.5543***	0.8868***	1.3543***	1.1427**	0.3116**	0.6965***	0.7519***	0.3835
UNRATE	0.0006	0.0007	0.0008	-0.0031***	0.0029**	0.0013	0.0003	-0.0024
SPREAD	0.0469	0.0044	0.0146	0.1384*	-0.0041	-0.0146	0.0514	0.2818**
UNC	0.0026	-0.0022	-0.0039	-0.0092*	-0.0042	-0.0098**	-0.0123***	-0.0215***
LEV	0.0412	-0.0482	-0.1180	-0.2469	0.1153	0.1068	0.2003	0.1985
MCAP	0.6801***	1.0683*	1.9081	2.3241	-0.7066	-0.7658	-1.0413*	-1.7091**
MTB	-0.0258**	-0.0315*	-0.0486*	-0.0969***	-0.0045	-0.0185	-0.0326**	-0.0093
R^2 Within	0.1373	0.1798	0.1784	0.1869	0.1035	0.1624	0.1550	0.1847
	Data Center				**Other**			
NPT	-0.1318	-0.1121	-0.1580	-0.1557	0.0603	0.0676	0.1438	0.1212
NPT_{t-1}	-0.3118***	-0.3107***	-0.2752***	-0.5885***	0.0232	-0.0303	-0.0253	-0.1716
SP500	0.4984***	0.9559***	0.9475	1.1449***	0.4666**	0.7929***	0.7946***	1.1011***
DFF	0.1109***	0.0874	0.1922***	0.1893***	-0.0257	-0.0523***	0.0143	0.0483
GDELT	-0.0123***	-0.0152**	-0.0134**	-0.0139***	-0.0012	-0.0001	-0.0039	-0.0072**
GDP	-0.2317	-0.5304	-0.3756*	-0.5368**	0.3989**	0.7145***	0.6008***	0.4615**
UNRATE	0.0006	-0.0035	-0.0059***	0.0047	0.0004	0.0002	0.0001	-0.0004
SPREAD	-0.1782***	-0.2152***	-0.1648	-0.2775***	0.0559	0.0798	0.1244	0.1875*
UNC	0.0063	0.0042*	-0.0012	-0.0058	-0.0008	-0.0053*	-0.0071	-0.0092*
LEV	-0.7025***	-0.6428***	-0.8998	-1.2330***	-0.0162	0.0542	0.0504	0.0369
MCAP	-6.0363***	-3.4430**	-3.5951**	-10.1213***	-0.5394**	-0.3198	-0.6078***	-0.8845***
MTB	0.1198***	0.0784***	0.0321	0.2073***	0.0060	-0.0075	-0.0161	-0.0216
R^2 Within	0.5986	0.5743	0.4765	0.7205	0.0683	0.1099	0.1125	0.1479

Note: The table reports panel OLS estimates of CAR over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings on governance level. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The sub-sector analyses in Tables 3.4 – 3.6 further confirm that ESG effects are not uniform across the REIT universe and that value relevance is tightly linked to economic characteristics of the underlying asset classes. Human- and service-intensive sectors such as lodging and health care show the clearest and broadest ESG reactions. The lodging sector exhibits significant positive effects in the [-3,3] and the [-5,5] windows for environmental and social sentiment. The asset class health care has positive significant CARs in the same windows for the environmental sentiment as well. The overall ESG results per sector, shown in Table 3.7, also show that the joint ESG sentiment in those asset classes is positively related to CARs in one window each. This is consistent with investors closely monitoring ESG language where day-to-day operations, tenant or patient contact, and reputational risk are particularly present (Liang et al., 2021). At the same time, negative coefficients for lagged ESG sentiment in health care (and other segments with significant lagged effects) suggest that persistent "good ESG news" in these sub-sectors may eventually reflect information that is already incorporated in prices or raise concerns about potential overstatement.

Energy- and capital-intensive asset classes such as industrial REITs likewise display positive reactions to ESG sentiment, with overall and environmental sentiment showing robust and economically intuitive effects in line with the importance of building efficiency, retrofit needs, and regulatory exposure for these properties. Residential REITs stand out by combining positive overall ESG effects (Table 3.7) with significant governance components in multiple windows which can be seen in Table 3.6. Here, decisions on rents, maintenance, and tenant treatment directly affect households and attract political scrutiny, so investors may view strong governance language as a credible signal of lower regulatory, reputational, and agency risk than in other property types. By contrast, retail REITs exhibit negative reactions to governance sentiment (Table 3.6), which is consistent with the sector facing ongoing structural challenges where emphatic governance language may be interpreted downplaying critical times rather than as pure good news. Data center REITs form another distinctive group, with consistently negative and highly significant coefficients across specifications. In a sector with very visible energy and climate concerns, investors appear particularly skeptical toward ESG language, echoing evidence that ESG sentiment is especially salient in industries with pronounced ESG controversies (Jeong et al., 2025).

Table 3.7 Regression Results on the Overall ESG and Sector-Level Sentiment

10-K/10-Q reports – ESG Overall – Sector-level								
	[-1,1]	[-3,3]	[-5,5]	[-1,10]	[-1,1]	[-3,3]	[-5,5]	[-1,10]
	Industrial				**Residential**			
NPT	-0.0018	-0.0242	-0.0279	0.0860***	-0.0090	0.0171	0.0392*	0.0094
NPT_{t-1}	0.0520	0.1454	0.1072**	0.0093	0.0064	0.0286	-0.0167	-0.0115
SP500	0.3955	0.7033	0.6194	0.1813	0.2898***	0.4064***	0.5313***	0.4047**
DFF	0.1202***	0.1691***	0.1732***	0.0725*	0.0190	0.0542	0.1227**	0.1393**
GDELT	-0.0013	-0.0055	-0.0038	-0.0092**	0.0002	-0.0004	-0.0030	-0.0019
GDP	-0.1567	-0.4543	-0.2693	-0.6020	-0.1242	0.1387	0.4838**	0.0843
UNRATE	0.0001	0.0020**	0.0021*	-0.0000	-0.0002	0.0004	0.0008	-0.0015
SPREAD	-0.0514	-0.1554***	-0.0866	-0.0972	0.0208	-0.0145	0.0308	0.1020
UNC	0.0001	0.0016	-0.0039	-0.0152*	0.0028*	0.0040	0.0023	-0.0008
LEV	-0.1251***	-0.1807***	-0.1897***	-0.3521***	-0.0167	-0.0461	-0.1247*	-0.1674**
MCAP	-0.8459***	-1.4009***	-1.0626***	-1.5903***	-0.2940	-0.7063**	-1.3097***	-2.6736***
MTB	-0.0044	-0.0047	-0.0102	-0.0191	-0.0190***	-0.0187***	-0.0107	-0.0280**
R^2 Within	0.1595	0.2432	0.1683	0.2897	0.1064	0.1066	0.1324	0.2237
	Lodging				**Health Care**			
NPT	-0.0413	0.1160*	0.0918	0.1208	0.0345	0.0676	0.1202*	0.0718
NPT_{t-1}	-0.1370	-0.2083	-0.3546	-0.2676	-0.2216**	-0.2053*	-0.2132	-0.2118**
SP500	0.8621	2.2896***	1.2843	1.6902***	0.3328*	0.6099***	0.6470**	0.8554***
DFF	-0.0611	0.0024	-0.0650	-0.0785	0.0103	-0.0289	0.0495	0.0659
GDELT	0.0108	0.0082	0.0113	0.0108	-0.0021	0.0004	-0.0029	-0.0069*
GDP	1.3484***	1.6651***	1.8768***	1.1047**	0.2495	0.2967	0.2616	0.1814
UNRATE	-0.0084	-0.0370***	-0.0137	0.0290**	-0.0050	-0.0172***	-0.0223***	-0.0077
SPREAD	0.2492***	0.4285***	0.5559***	0.5638***	0.0206	-0.0243	0.0076	0.2555***
UNC	-0.0070	-0.0122*	-0.0144*	-0.0209***	-0.0029	-0.0064	-0.0072*	-0.0146***
LEV	0.2599*	0.5206***	0.5032***	0.4773**	-0.1656***	-0.1727	-0.1832	-0.2440**
MCAP	-0.1427	0.1369	-0.0123	0.1012	-1.1469**	-2.5176***	-2.9692***	-3.1908***
MTB	0.0063	-0.0377***	0.0042	-0.0090	0.0119**	0.0189	0.0241	0.0203*
R^2 Within	0.1232	0.2932	0.1603	0.2468	0.1368	0.2206	0.2151	0.2665
	Office				**Retail**			
NPT	0.0537	0.0721	0.2102	0.1826	-0.0103	0.0147	0.0154	0.0518
NPT_{t-1}	-0.0597	-0.0211	-0.1429	-0.1282	-0.0398	-0.0303	0.0181	-0.0609
SP500	0.5550***	0.9948***	1.0944**	1.5781***	0.1632	0.6695**	0.5869**	0.9175***
DFF	0.0274	-0.0064	0.1142	0.1299	0.0119	0.0023	0.0705*	0.0691*
GDELT	-0.0004	0.0023	-0.0011	-0.0049	0.0022	0.0043	0.0048	0.0017
GDP	0.5555***	0.8971***	1.3530***	1.1478**	0.3244**	0.6963***	0.7558***	0.3784
UNRATE	0.0006	0.0007	0.0007	-0.0031***	0.0028**	0.0014	0.0003	-0.0024
SPREAD	0.0472	0.0073	0.0164	0.1413*	0.0024	-0.0115	0.0548	0.2825**
UNC	0.0024	-0.0024	-0.0045	-0.0098*	-0.0035	-0.0094**	-0.0119***	-0.0211***
LEV	0.0399	-0.0584	-0.1153	-0.2522	0.1148	0.1124	0.2135	0.1965
MCAP	0.7058***	1.1356*	1.9455	2.3620	-0.6885	-0.6981	-0.9401	-1.6188**
MTB	-0.0269**	-0.0359**	-0.0508*	-0.0995***	-0.0044	-0.0198*	-0.0347**	-0.0103
R^2 Within	0.1404	0.1822	0.1864	0.1903	0.0924	0.1519	0.1482	0.1785
	Data Center				**Other**			
NPT	-0.1612***	-0.1370***	-0.1655	-0.1287**	-0.0516	0.0077	0.0007	0.0101
NPT_{t-1}	-0.9405***	-0.9496***	-1.0057	-1.3728***	0.0531	0.0512	0.0133	-0.1908
SP500	0.5074***	0.9651***	0.9487	1.2263***	0.4724**	0.7970***	0.7971***	1.1024***
DFF	0.1139***	0.0892***	0.1949***	0.1940***	-0.0248	-0.0510***	0.0138	0.0456
GDELT	-0.0131***	-0.0159**	-0.0142*	-0.0141***	-0.0010	0.0000	-0.0035	-0.0068**
GDP	-0.1108	-0.4112	-0.2659	-0.3274*	0.4354**	0.7445***	0.6172**	0.4615**
UNRATE	0.0013***	-0.0028***	-0.0051**	0.0070***	0.0003	0.0001	-0.0000	-0.0005
SPREAD	-0.1644***	-0.2010***	-0.1524	-0.2443***	0.0664	0.0861	0.1273	0.1861*
UNC	0.0062	0.0042	-0.0014	-0.0064	-0.0009	-0.0053*	-0.0073	-0.0094**
LEV	-0.6539***	-0.5830***	-0.8331	-1.1491***	-0.0187	0.0435	0.0444	0.0387
MCAP	-6.1283**	-3.4724**	-3.6726**	-10.0342***	-0.3423	-0.1675	-0.4341	-0.7929**
MTB	0.1059*	0.0608*	0.0144	0.1909***	0.0031	-0.0077	-0.0190	-0.0246
R^2 Within	0.6548	0.6188	0.5023	0.7362	0.0606	0.1043	0.1032	0.1467

Note: The table reports panel OLS estimates of CAR over the event windows ([-1,1], [-3,3], [-5,5], [-1,10]) for 10-K/10-Q filings on the overall level. All specifications include firm fixed effects and time fixed effects, with two-way clustered standard errors (by firm and time). R2 within is reported. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Together, these patterns show that ESG sentiment is rewarded most strongly in sub-sectors where ESG issues are closely tied to operating models and that the direction and strength of the effects differ systematically across asset classes rather than reflecting a single, market-wide ESG premium. This asset-class-specific heterogeneity provides empirical support for H3 and underlines why REITs offer a particularly suitable setting for our analysis, as their standardized structures and clearly distinguishable property types allow ESG–return relationships to be studied in a granular, economically meaningful way.

3.6 Conclusion

This study examines how investors respond to ESG-related sentiment in mandatory and voluntary corporate disclosures of U.S. equity REITs. Using RoBERTa as an advanced LLM, we extract ESG pillar-specific sentiment from 10-K and 10-Q filings as well as standalone ESG reports between 2016 and 2025 and relate these measures to CARs around disclosure dates. Our results provide evidence on how investors process ESG narratives across disclosure channels, ESG pillars, and REIT sub-sectors. Overall, the results suggest that ESG communication in REIT markets is processed selectively rather than as a uniform signal. This highlights the importance of disaggregated approaches when assessing the role of (ESG) disclosures in real estate capital markets.

Overall sentiment within mandatory filings is associated with short-term market reactions. The aggregate ESG level obscures effects that show up clearly, when disaggregating the reports by pillar and sector. For the ESG reports, only the social pillar shows negative CAR reactions to the sentiment. Additional information on ESG matters might show overinvesting and potential ‘green washing’ which is then penalized by investors or simply ignored. In the mandatory filings, environmental and social sentiment exhibit economic relevance, governance-related sentiment is largely insignificant, suggesting limited incremental information content beyond what is already captured by the REIT regulatory framework and standard governance structures. In the pillar-level results, environmental sentiment stands out as the most stable and significant CAR driver, followed by social- and then by governance-related managerial sentiment. The results also reveal substantial heterogeneity across REIT sub-sectors. Environmental sentiment is particularly relevant for lodging, health care, and residential REITs, where energy efficiency and operating intensity directly affect NOI, while social sentiment plays a more pronounced role in sub-sectors with high levels of human interaction (e.g. also lodging). Governance sentiment shows mixed results within property types.

From a managerial perspective, the findings suggest that ESG communication strategies should be straightforward and closely aligned with the underlying property portfolio. Simply increasing the positivity of ESG-related language, particularly in voluntary disclosures, does not lead to more favorable market responses and may even cause skepticism in some asset classes. More specific, credible, and economically grounded disclosures are more likely to signal effective risk management and long-term asset quality.

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4 The Non-Linear Dynamics of Disclosure Tone and REIT Bond Yields

4.1 Abstract

The tone in corporate disclosures represents a source of information for bond investors that complements quantitative information, allows to predict a firm's default risk and subsequently bond yields. However, previous studies investigating the predictive value of disclosure tone for bond yields assume a linear relationship. We argue that linearity cannot be assumed and hypothesize two dimensions of non-linearity in the tone-yield relationship. In our empirical investigation, we employ a multi-method approach combining machine learning methodologies and conventional regression analysis. Using a sample of 64 bond-issuing equity REITs over the period of 2011 to 2024, we provide evidence that the relationship of disclosure tone and bond yield spread is non-linear. Net positive tone, which jointly accounts for positive and negative disclosure tone in REIT financial statements, has a quadratic relationship with future REIT bond yield spread. The more positive or negative disclosure tone is, the higher are future bond yield spreads. Additionally, net positive tone explained by REIT fundamentals negatively predicts bond yield spread in the next month while non-fundamental tone positively predicts it. Our findings suggest that the disclosure tone-bond yield relationship is more complex than assumed by previous studies.

Keywords: Corporate Bonds, REITs, Corporate Disclosures, Textual Tone, Machine Learning

4.2 Introduction

When assessing the credit risk of a firm, bond market investors are faced with informational asymmetries between themselves and firms issuing bonds, which can explain bond yields (Han and Zhou, 2014; Duffie and Lando, 2001). One issue is that accounting information provided by firms to bond investors and credit analysts to assess default risk is incomplete and infrequent (Duffie and Lando, 2001). An emerging literature provides evidence that not only *what information* a firm's management discloses (Gupta et al., 2025; Lou, 2019), but also *how* it is disclosed matters for bond market participants. In particular, the tone in corporate disclosures has been found to predict the default risk of firms (Jin et al., 2024) and bond investor behavior (Cao et al., 2025). This suggests that disclosure tone signals risk-related information to bond investors and represents an additional source of information improving the information environment around a firm.

However, previous studies assume a linear relationship between disclosure tone and bond yields (Schmeling and Wagner, 2025; Hirsch et al., 2024; Wang, 2020). The question of whether the relationship is indeed linear arises for the following reasons: First, considering their focus on assessing a firm's default risk and the limited upside potential of fixed income securities, bond investors have been found to have a greater demand for negative information (De Franco et al., 2009) and are more sensitive to the negative or pessimistic tone in corporate disclosures (Jin et al., 2024). Consequently, bond investors are likely to favor a mildly negative tone in financial statements as it indicates a managerial dedication to transparency and higher disclosure quality, which in turn is expected to lead to lower bond yields. This expectation is in line with previous findings for the stock market, where a change to a more pessimistic disclosure language has been found to predict lower cost of equity (Iatridis, 2016).

However, as negative tone in financial statements increases, bond investors may consider it as a signal for an increased default risk, which is expected to result in higher bond yields. Furthermore, overly optimistic tone may signal risk-related information to bond investors with regards to a firm's litigation risk, future performance and managerial disclosure practices. With regards to this first dimension of non-linearity, we hypothesize a quadratic tone-bond yield relationship. In particular, we expect a mildly negative or neutral tone to reduce the bond yield spread, and an overly positive or negative tone to increase it.

Second, previous studies on the tone-bond yield relationship use aggregated tone measures, which ignores that tone can be either based on firm-fundamentals or not. An optimistic or pessimistic tone that is explained by firm fundamentals may signal information to bond investors about a firm's dedication to transparency and disclosure

quality and reduce their required yield. An overly negative or positive disclosure tone not explained by fundamentals may signal information about a firm to bond investors that positively impacts their risk perception and required yield. Furthermore, the informative value of fundamentals-based disclosure tone may be limited considering the availability of quantitative information capturing this information. Tone that is not based on firm-fundamentals, on the other hand, may capture new information for bond investors and thus have a higher informative value. With regards to this second dimension of non-linearity, we expect the fundamentals-based tone to reduce bond yield and the non-fundamental tone to increase it. Additionally, we hypothesize non-fundamental tone to have more predictive value for the bond yield than fundamentals-based tone.

In our empirical investigation, we focus on net positive tone, which jointly accounts for positive and negative disclosure tone. We follow Kozak et al. (2026) and use publicly traded equity Real Estate Investment Trusts (REITs) that issue bonds as a laboratory for the following reasons: First, equity REITs represent companies that focus on the investment in, development and management of income-producing real estate. The property portfolios owned by REITs generate more stable cash flows compared to firms focused on products and services as well as allow bond investors to assess the credit risk of REITs more easily. Thus, the homogeneity of equity REITs in terms of business model allows eliminating the effects of, for example, differing levels of cash flow uncertainty, fixed assets or business focus among firms in an industry on bond yields.

Second, while covenants are uncommon in the investment grade bond market for non-REIT firms, covenants relating to, amongst others, secured and overall debt ratios, unencumbered assets, and debt service coverage ratios are standard for all REIT bonds (e.g., Riddiough and Steiner, 2020; Deng et al., 2016). Riddiough and Steiner (2020) provide evidence for the value of bond covenants to alleviate agency conflicts between REIT management and shareholders. The presence of standardized bond covenants across the REIT industry allows us to mitigate any effects on bond yields that stem from variations in bond covenants or their absence across firms as well as agency conflicts.

Third, REITs are limited in their ability to retain earnings due to their high dividend payout requirement, which in turn results in a higher reliance on external financing than non-REIT firms (Ott et al., 2005), a higher transparency in terms of disclosure (Danielsen et al., 2014) and higher monitoring by external sources. Additionally, equity REITs have a comparatively higher institutional ownership (e.g., Devos et al., 2012; Ciochetti et al., 2002), which enhances corporate governance (Hartzell et al., 2014; Chung et al. 2012; Feng et al., 2010; Hartzell et al., 2006) and the informativeness of disclosure tone (Jain et al., 2023). Thus,

the institutional characteristics of equity REITs ensure a certain industry-level baseline of disclosure quality that is less likely present in other industries.

We use a multi-method approach combining machine learning and conventional regression approaches in our analysis. First, we employ a large language model approach (RoBERTa) to extract tone measures from the financial statements (10-Q and 10-K) for 64 equity REITs over the period of 2011 to 2024. In particular, we extract quarterly positive (optimistic) and negative (pessimistic) measures to calculate a net positive tone measure for each REIT in our sample. Next, we use a two-way fixed effects regression to analyze the first dimension of non-linearity. To investigate the presence of a quadratic term in the tone-yield relationship, we employ an eXtreme Gradient Boosting (XGBoost) algorithm in combination with SHapley Additive exPlanations (SHAP) values and Accumulated Local Effects (ALE) plots. To assess the second dimension of non-linearity, we disaggregate our tone measures by regressing them on firm fundamentals and retaining fitted values (fundamentals-based tone) and residuals (non-fundamental tone). We then use disaggregated tone measures in our two-way fixed effects regression.

We find the tone-yield relationship to be non-linear across the two dimensions investigated: First, we provide evidence that net positive tone has a quadratic relationship with the REIT bond yield spread in the next month. Second, fundamental and non-fundamental net positive tone predict future REIT bond yield spread in different directions. While fundamentals-based net positive tone negatively predicts the REIT bond yield, the non-fundamental net positive tone positively predicts it. Furthermore, we show that the non-fundamental component of disclosure tone has a higher informative value to bond investors than the fundamentals-based component.

Our study contributes to the literature in several ways: We contribute to a larger finance and accounting literature that investigates the informative value of tone in corporate disclosures for corporate and sovereign bond markets (Cao et al., 2025; Schmeling and Wagner, 2025; Hirsch et al., 2024; Jin et al., 2024; Liang et al., 2023; Wang, 2020) by showing that the tone-bond yield relationship is not linear. To our knowledge this is the first study to investigate the assumption of linearity made by previous studies by 1) separating tone into a fundamental and non-fundamental component and 2) accounting for a quadratic relationship with bond yields.

Additionally, we contribute to the REIT bond literature, which compared to REIT stocks, is relatively small and has focused on factors such as commercial real estate market sentiment (Freybote, 2016), environmental performance (Eichholtz et al., 2019), ownership structure (Gilstrap et al., 2022), debt covenants (Deng et al., 2016), debt capital structure decisions

(Allen and Letdin, 2020), and real estate-specific factors (Kozak et al., 2026) in the context of REIT bonds.

Last, our study contributes to an emerging literature on textual analysis in the context of commercial real estate (e.g., Carstens and Freybote, 2021; Beracha et al., 2019; Hausler et al., 2018), REITs (e.g., Paulus et al., 2022; Kim et al., 2023; Hausler et al., 2018) and housing markets (e.g., Aroul et al., 2025; Shen and Ross, 2021; Nowak et al., 2021; Nowak and Smith, 2017). To our knowledge, this is the first study that employs textual analysis in the context of REIT bonds.

Our findings have implications for REIT management and bond investors. Our results suggest that the tone in REIT financial statements can be used as an additional source of information by bond investors to predict yields – irrespective of whether it is based on fundamentals or not. Our findings for non-fundamental tone suggest that REIT management should pay particular attention to align their disclosure tone with firm fundamentals. Furthermore, the quadratic relationship identified for net positive tone suggests that overly positive or negative tone in disclosures should be avoided by management.

The remainder of this study is structured as follows. Next, we review relevant studies on corporate disclosures and bond markets to develop our theoretical framework and hypotheses. It is followed by a discussion of our data, tone measure derivation and methodology. Then, we present our results and a conclusion.

4.3 Literature Review and Hypothesis Development

4.3.1 Disclosure and Bond Markets

An emerging literature investigates the informative value of qualitative or soft information in disclosures for sovereign and corporate bond markets. Some studies focus on *what information* is revealed in textual disclosures such as the use of derivatives (Gupta et al., 2025) or pending lawsuits (Lou, 2019). For example, Bozanic et al. (2023) use textual analysis to investigate how credit analysts use qualitative information in corporate financial statements to assess credit risk. They find evidence that credit analysts account for qualitative (soft) information in their credit ratings. In particular, they make soft adjustments when companies provide more disclosures that reflect increases in credit risk (e.g., credit risk and debt) or decreases in credit risk (profitability and managerial outlook). The authors conclude that textual sections in annual reports provide complementary information to the private information credit analysts already have. Other studies focus on

how information is disclosed, i.e., readability and textual sentiment/tone. With regards to our study, this latter stream of literature is most relevant.

Several studies have investigated readability in corporate disclosures as a dimension of how firms provide bond market participants with information: Chen and Tseng (2021) analyze the readability of the narrative "Notes to Consolidated Financial Statements" and its impact on corporate bond yields. They show that a lower readability predicts greater corporate bond yield spreads, particularly for firms in certain industries (high-tech) and with a higher equity volatility. Bonsall and Miller (2017) show that corporate disclosures with a lower readability are associated with a lower credit rating, higher disagreement between bond rating agencies and cost of debt. Chen et al. (2024) further investigate the impact of disclosure readability on corporate bond yields. The authors focus on narrative pension disclosures by firms and its association with credit risk. They find supportive evidence that a lower readability predicts higher bond yield spreads. Farrell et al. (2024) focus on the municipal bond market and show that the complexity of disclosures impact cost of debt for municipalities. It is noteworthy that the authors find the positive relationship for complexity and borrowing costs to be particularly strong for municipalities with a poorer information environment due to less complementary information from rating agencies.

Another stream of literature focuses on the impact of tone in news or disclosures by firms or governmental agencies on bond markets. Consoli et al. (2021) investigate emotions in macroeconomic news and show that they have predictive power for sovereign bond yield spreads. In particular, they find that negative emotions in the news can predict yield spreads in periods of distress. Hirsch et al. (2024) provide evidence that the tonality of television news impacts sovereign debt spreads. Hereby, positive (negative) news predict a lower (higher) spread.

Wang (2020) uses textual analysis to analyze the impact of the tone in risk disclosures in financial statements on Credit Default Swaps (CDS). The author finds a change in CDS spreads that is positively associated with the pessimistic tone in risk disclosures. Tone hereby is distinct from the amount of disclosures. However, the market reaction to disclosure tone is stronger for entities closer to default, i.e., a higher concern of downside risk, and with weaker information environment. Overall, the author concludes that the tone in MD&A risk disclosures has informative value for debt and CDS market investors. Liang et al. (2023) show that a more pessimistic managerial tone in financial statements predicts the hedging behavior of investors in the CDS market.

Jin et al. (2024) investigate the informative value of the tone, besides length and content, of risk disclosures in financial statement for a firm's default risk. They provide evidence for

the predictive power of tone for a firm's default risk, particularly in the post-GFC period. In particular, negative tone positively predicts default risk. The relationship is stronger for firms that, for example, are undergoing shifts in default risk, face financial distress or have heightened scrutiny from external monitors. The authors conclude that the tone in risk disclosures in annual report have informative value for bond investors to assess default risk. Cao et al. (2025) investigate whether insurance companies, which are the largest investor type in investment-grade corporate bonds, use the tone of earnings calls as a source of information in their trading of BBB- rated bonds. The authors find that negatively toned earnings calls have predictive power for the selling behavior of insurance companies. Schmeling and Wagner (2025) find that the tone used by the Central Bank in its communications can predict equity and capital market outcomes. In particular, they find positive tone to predict, amongst others, lower credit risk spreads. Rich et al. (2021) investigate disclosure tone in the context of municipal bonds and find the negative tone in the MD&A section to positively predict cost of debt and disagreements between bond rating agencies.

4.3.2 Hypotheses Development

While some studies investigating disclosure tone in the context of bond markets find positive and negative tone to have predictive value (Schmeling and Wagner, 2025; Hirsch et al., 2024), previous studies on bond markets in general and corporate bonds in particular emphasize the importance of negative or pessimistic tone for bond market participants (Cao et al., 2025; Jin et al., 2024; Liang et al., 2023; Consoli et al., 2021; Wang, 2020). The higher sensitivity to negative tone in corporate disclosures and a greater demand for negative information (De Franco et al., 2009) results from the limited upside potential of corporate bonds and need of bond investors to assess risks to predict a firm's default risk.

The focus of bond investors on negative or pessimistic tone differs from the focus of corporate management, which has been found to prefer a positive disclosure tone over a neutral or negative (Brockman et al., 2015; Price et al., 2012; Schleicher and Walker, 2010; Rutherford, 2005; Hyland, 1998; Hildebrandt and Snyder, 1981). The managerial positivity bias results from the ability of positive framing to influence the reaction and perception of stock market investors (e.g., Huang et al., 2014; Davis et al., 2012; Henry, 2008). Kartik et al. (2007) develop a "costly talk" model in which credulous investors believe in inflated communication such as recommendations by analysts and take corresponding actions. However, sophisticated investors are able to decode the inflated communication and be not influenced by it in their actions. Thus, misleading or overly inflated information in communication impacts the responses of sophisticated and credulous investors in opposite

directions, and the offsetting gains and costs of inflated communication need to be considered by the sender (e.g., equity analysts).

As a consequence, sophisticated institutional investors, which represent the predominant bond investor type (De Franco et al., 2020), can be assumed to be less likely influenced by an inflated or overly positive tone. In fact, institutional investors in the stock market have been found to penalize firms for an overly optimistic tone in disclosures (Baginski et al., 2018; Blau et al., 2015; Tan et al., 2014). These sophisticated stock market investors can identify when the tone in corporate disclosures fails to match the quantitative information about a firm's performance and firms use tone management. Another explanation is that an overly optimistic tone signals information about firm risks as it has been found to negatively predict a firm's financial performance (Jiang et al., 2019; Huang et al., 2014) as well as positively predict litigation risk (Rogers et al., 2011). Therefore, Iatridis (2016) shows that a change in reporting language to a more pessimistic or unexpectedly pessimistic language predicts lower cost of equity.

Considering the findings of previous studies on institutional investors, who are the predominant type of investor in the bond market (De Franco et al., 2020) and disclosure tone, we expect the negative tone in REIT financial statements to have a higher predictive value for bond yield spreads than the positive tone. However, previous studies investigating tone and bond yield or CDS spreads (Schmeling and Wagner, 2025; Hirsch et al., 2024; Wang, 2020) assume a linear relationship. We argue that two dimensions of non-linearity exist in the relationship of tone, defined as net positive tone, and bond yield spread:

First, considering that institutional investors are aware of the managerial positivity bias, they may consider a mildly negative or neutral tone in REIT disclosures a signal of a firm's commitment to a high level of transparency and absence of tone management. Consequently, they may require a lower yield, which is in line with the findings of Iatridis (2016) for the stock market. An increase in negative or positive disclosure tone, however, is likely to signal an increase in risks to bond investors and increases their yield requirements. Thus, we expect a quadratic relationship between net positive tone and REIT bond yield spread.

Second, the tone in REIT financial statements has two components: The first component can be explained with firm fundamentals such as operating performance, firm size, leverage, stock market performance, or growth opportunities. The second component cannot be explained with firm fundamentals, but other factors such as managerial sentiment or private information not captured by firm fundamentals. Previous studies on

disclosure tone in the context of bond markets (Cao et al., 2025; Schmeling and Wagner, 2025; Hirsch et al., 2024; Jin et al., 2024; Liang et al., 2023; Wang, 2020) fail to make this distinction in their analysis.

Fundamentals-based net positive tone is expected to reduce bond investor risk perceptions and negatively predict the bond yield spread, while a net positive tone that is not explained by firm fundamentals may signal information to bond investors about managerial disclosure practices (e.g., tone management, transparency) and increase their risk perception. This expectation is in line with previous studies on institutional investors in the stock market, who penalize firms for an overly positive tone in their disclosures (Baginski et al., 2018; Blau et al., 2015; Tan et al., 2014). Therefore, we expect a positive relationship of non-fundamental tone and REIT bond yield spread.

Furthermore, non-fundamental tone may represent new information and thus have a higher informative value for REIT bond investors as it is not captured by fundamental variables, for which quantitative data commonly exists. Therefore, we hypothesize that tone not explained by fundamental variables has a higher predictive value for REIT bond yields than the fundamentals-based negative tone.

4.4 Data

4.4.1 Derivation of Tone Measures

We obtain the quarterly financial statements (10-Q and 10-K) for publicly traded equity REITs over the period of 2011 to 2024, thereby covering multiple regime changes in credit and financial markets. The beginning of our sample period is due to limited REIT bond transaction data prior to 2011 (Freybote, 2016). Considering not all equity REITs access the bond market, we only focus on equity REITs that issued publicly traded bonds over the sample period. Of the 174 REITs that were NAREIT index constituents at any time between 2011 and 2024, 89 REITs issued bonds. Due to missing financial statements for some REITs, our final sample consists of 64 REITs.

We focus on the Management and Discussion Analysis (MD&A) section of financial statements in line with previous studies (e.g., Wang, 2020; Koelbl, 2020) to extract our tone measures. In this section, REITs are required to discuss their financial condition, results of operations, liquidity and known trends or uncertainties that could impact future performance. As a robustness check, we also obtain our tone measures based on all textual sections in financial reports.

We derive our tone measures using the RoBERTa (Robustly Optimized BERT Pretraining Approach) model by Liu et al. (2019), an improved version of BERT (Bidirectional Encoder Representations from Transformers) introduced by Devlin et al. (2019). These models are Large Language Models (LLMs) and represent a state-of-the-art approach in natural language processing (Karanikola et al., 2023). The use of the RoBERTa model minimizes the need for an adequate training dataset, as the model comes pre-trained and is only optimized for an individual case (Liu et al., 2019). In our case, the model is optimized using the SEntFiN 1.0 dataset by Sinha et al. (2022).

The preprocessing of financial statements is crucial, as the model requires clean tokens to accurately classify tone. Therefore, we employed techniques commonly used in the literature, such as segmenting the report into smaller paragraphs, converting all words to lowercase, and removing numbers and punctuation. The final pre-processing step is lemmatization, where words are transformed into their root forms to reduce the complexity and size of the vocabulary of the textual data (Paulus et al., 2025).

Our approach to using RoBERTa for tone classification results in a probabilistic output with values ranging from 0 to 1, where values close to 0 indicate a low probability of a message being positive and vice versa. To achieve a three-way classification, we deploy a decision rule in line with Paulus et al. (2025) given as:

$$P \geq 0.667 \rightarrow \text{positive tone}$$

$$0.333 < P < 0.667 \rightarrow \text{neutral tone}$$

$$P \leq 0.333 \rightarrow \text{negative tone}$$

After classifying the tone of the segments in the financial reports, we aggregate it monthly to construct our three tone measures. The first measure, the Optimism Indicator (*OI*), is based on Antweiler and Frank (2004) and captures the positive disclosure tone as shown in Equation 4.1.:

$$OI_t = \frac{\sum_1^I positive\ segments_{i,t}}{\sum total\ number\ of\ segments_t}, \tag{4.1}$$

where i denotes the number of segments of a financial report and t denotes the quarter the report was published.

The second measure is called Pessimism Indicator (*PI*), captures negative disclosure tone and measures the number of negative segments in relation to the total number of segments as shown in Equation 4.2:

$$PI_t = \frac{\sum_1^I negative\ segments_{i,t}}{\sum total\ number\ of\ segments_t}. \quad (4.2)$$

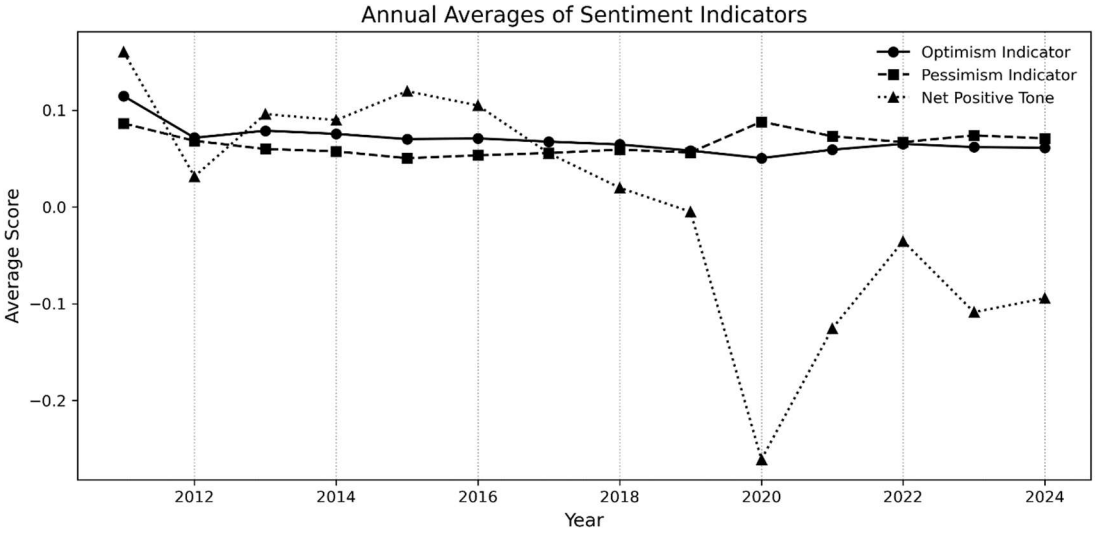
To derive a tone measure that jointly accounts for positive and negative tone, we calculate the Net Positive Tone (*NPT*) in line with Doran et al. (2012) as shown in Equation 4.3. *NPT* ranges from -1 to 1, where values below 0 indicate a tendency toward a generally negative tone and values above 0 indicate a tendency toward a more positive overall tone.

$$NPT_t = \frac{(\sum_1^I positive\ segments_{i,t} - \sum_1^I negative\ segments_{i,t})}{(\sum_1^I positive\ segments_{i,t} + \sum_1^I negative\ segments_{i,t})}. \quad (4.3)$$

Please note, our tone measures are in levels as opposed to changes to account for the fact that bond market investors are expected to respond to the disclosure tone of the most recent financial statement as opposed to the change in disclosure tone from the previous quarter. Kravet and Muslu (2013) use changes in risk disclosure tone to account for omitted variables and reverse causality resulting from repetitions in risk disclosures by firms over multiple quarters. However, compared to risk factors discussed by firms, which are more likely to remain constant over a certain amount of time, the content of MD&A sections varies from quarter to quarter as it reflects the most recent operations, financial conditions, and expectations for future performance. Furthermore, we address endogeneity concerns due to omitted variables or reverse causality by using a fixed effects regression and lagged tone variables in our empirical analysis.

Figure 4.1 graphs our tone measures, averaged per year across REITs in our sample, for the period of 2011 to 2024. The *OI* is above the *PI* for all periods until 2020, which can be explained by factors such as favorable economic conditions and/or a positivity bias in financial statements (Schleicher and Walker, 2010). Since 2020, the *PI* exceeded the *OI* due to events such as COVID-19 pandemic and shift interest rate regime. Figure 4.1 emphasizes the importance of jointly assessing positive and negative tone in form of the net positive tone (*NPT*) measure and motivates our focus on this balanced tone measure. While the average positive and negative scores appear to be relatively levelled over time, the *NPT* shows considerable variability: Since 2015, the average annual net positive tone has been decreasing, i.e., became less positive, and in 2019 fell below 0, which means it became negative. For the remainder of our sample period, it remained in the negative range.

Figure 4.1 Positive, Negative, and Net Positive Tone Measures over Time



To assess whether cross-sectional differences exist between REITs with different property type specializations, Table 4.1 reports average values of the sentiment measures for diversified, health care, hotel & resort, industrial, office, residential, retail, and specialized REITs. Both *OI* and *PI* are positive across all asset classes. Only industrial and specialized REITs exhibit a positive *NPT*, whereas all other sectors show a negative NPT. While the levels of *OI* and *PI* are similar across sectors, *NPT* displays greater variation, with the most negative values observed for hotel & resort and office REITs. Overall, however, there is no indication of pronounced cross-sectional differences.

Table 4.1 Sentiment REIT Property Types

GICS Industry Name	Number of REITs	OI	PI	NPT
Diversified REITs	6	0.0741	0.0846	-0.0890
Health Care REITs	5	0.0553	0.0722	-0.1409
Hotel & Resort REITs	6	0.0360	0.0472	-0.2279
Industrial REITs	5	0.0567	0.0500	0.0820
Office REITs	8	0.0376	0.0558	-0.2141
Residential REITs	9	0.0640	0.0681	-0.0284
Retail REITs	9	0.0601	0.0633	-0.0443
Specialized REITs	16	0.0860	0.0712	0.0849

4.4.2 Dependent Variable and Control Variables

Our dependent variable is the spread of REIT bond yields over U.S. Treasuries of the same maturity. Data on REIT bond yields are sourced from the Trade Reporting and Compliance Engine (TRACE) database by FINRA, which has required broker-dealers to self-report their

over-the-counter bond transactions since 2002.[2] We calculate monthly yield spreads by averaging the volume-weighted yields of all transactions in a month of a given REIT bond and then subtracting the yield on U.S. Treasuries with corresponding maturities. We obtain U.S. Treasury data from the Liu and Wu (2021) dataset. Our final sample consists of 30,172 monthly bond yield spreads of U.S. equity REITs that were constituents of the FTSE NAREIT Index at some point between January 2011 and December 2024.[3]

While our tone measures are our independent variables of interest, we control for several variables that impact bond yields: First, we consider the features of REIT bond issues. Since TRACE does not offer bond characteristics such as the bond maturity date, call features, or coupon rate, this data was manually collected from the FINRA website, which is based on the TRACE database. In particular, we control for bond features such as the coupon rate, bond price, transaction volume, time to maturity, call option and credit rating of the issuing REIT. Bond transactions with missing data are excluded. Additionally, bonds with maturities of less than one month and those with maturities of more than 360 months are excluded, as no Treasury matching was feasible. Following Bessembinder et al. (2009), TRACE data entries marked as canceled are removed from the dataset, while corrected entries are kept.

Furthermore, we also control for variables capturing the liquidity of REIT bonds by including the percentage of days in the month that the bond was not traded (*Bond Zero Trading Days*), the percentage of days in a month on which no outstanding bond a REIT was traded (*Firm Zero Trading Days*) and the monthly mean of the difference in the average daily bid and ask prices of each bond (*Bid-Ask Spread*).

The readability and similarity of financial statements have been identified as potential concerns about financial disclosure by previous studies (e.g., Abbassi et al., 2025; De Franco et al., 2020; Li, 2019; Dyer et al., 2017; Bonsall et al., 2017). In particular, several studies emphasize the importance of readability of corporate disclosures in the context of bond yields (Chen et al., 2024; Chen and Tseng, 2021; Bonsall and Miller, 2017). We control for them as follows: For readability, we use the Gunning Fog Index from Wharton Research Data Services (WRDS) following Lee (2008) and Lawrence (2013) to capture text complexity. For similarity, we use a cosine similarity measure obtained from the WRDS SEC

[2] As bonds are traded over-the-counter (OTC), data collection on bond transactions is limited compared to equity trading data. TRACE is the most relevant database for researching bond transactions in the US. However, its nature of self-reporting can lead to erroneous entries. By preprocessing and winsorizing our data, we try to ensure that such errors do not distort the data.

[3] To prevent survivorship bias, our analysis includes all REITs that issued bonds during the study period, regardless of whether they were present for the entire duration of the sample.

Analytics Suite. This measure captures the extent to which a disclosure resembles prior filings and is established in the REIT literature (Paulus et al., 2022).

In our model, we include several REIT-level characteristics: We control for REIT size measured as the log of market capitalization, stock market performance measured by a REIT's stock market return, operating performance captured by Funds from Operations (*FFO*), leverage defined as total debt divided by total assets, dividends per share, and growth opportunities as measured by the market to book ratio. Furthermore, we also include the long-term debt of the REITs. We additionally control for the property type specialization of REITs using binary variables with diversified REITs being the reference group. Monthly REIT market and quarterly REIT accounting data are obtained from Compustat and Refinitiv Eikon.

Last, we control for stock market, bond market and macroeconomic conditions that impact bond yields: We control for stock market conditions by including the return on the S&P 500 index as well as the CBOE volatility index (*VIX*). Bond market conditions are controlled for with the term structure defined as spread between the 10-year U.S Treasury and 3-month Treasury Bill as well as the credit risk defined as the spread between corporate bonds rated Baa and Aaa by Moody's. Macroeconomic conditions are controlled for with the interest rate volatility defined as the standard deviation of the monthly 3-month constant maturity Treasury rate over a 12-month period prior to a bond's transaction date, the unemployment rate and gross domestic product (*GDP*). Macroeconomic data are from the Federal Reserve Economic (FRED) monthly database, as presented by McCracken and Ng (2016). Table 4.2 presents an overview and description for our variables.

Table 4.2 Variable Description

Variable	Description
Dependent Variable	
Bond Yield Spread	Difference between the volume-weighted yield to maturity of the REIT bond and the maturity-matched Treasury yield to maturity
Tone and Disclosure Variables	
Optimism Indicator	Number of positive segments in a 10-Q report divided by total segments
Pessimism Indicator	Number of negative segments in a 10-Q report divided by total segments
Net Positive Tone	Number of positive minus negative segments in a 10-Q report divided by the total number of positive and negative segments
Similarity	Cosine similarity from WRDS between the current 10-Q report and the previous 10-Q report
Readability	Gunning Fog Index of the 10-Q report capturing readability and textual complexity
Bond Variables	
Coupon Rate	Coupon rate on bond in percent
Bond Price	Bond price inclusive of any commission, mark-ups and/or mark-downs
Transaction Volume	Volume reported on the trade
Time to Maturity	Difference in months between maturity date and transaction date
Credit Rating Dummy	1 if investment grade bond, 0 if high yield bond
Call Status Dummy	1 if callable, 0 if not
Liquidity Variables	
Bond Zero Trading Days	Percentage of days in the month that the bond was not traded
Firm Zero Trading Days	Percentage of days in a month on which no outstanding bond of a REIT was traded
Bid-Ask Spread	Monthly mean of the difference in the average daily bid and ask prices of each bond
REIT-Specific Variables	
Property Type Dummy	8 REIT sectors based on property portfolio, defined by NAREIT, reference category is Diversified
Market Capitalization	Measure of company size, expressed as total dollar market value of a REIT's outstanding shares of stock (in million USD), as log
Return	Expressed as the current adjusted price of the REIT stock minus the original adjusted price of the stock (month t-1) divided by the original adjusted price
Funds From Operations	Cash flow from operations
Leverage	Total debt outstanding divided by total assets
Dividends per Share	Distribution of a REIT's earnings per share to its shareholders
Market-to-Book	Market capitalization divided by total assets minus total outstanding debt
Long-term Debt	Long-term debt, measured as the book value of a firm's long-term debt
Equity Market Variables	
S&P 500	Return of the S&P 500 composite index
VIX	CBOE volatility index
Macroeconomic Variables	
Term Spread	10-Year Treasury rate minus 3-Month Treasury Bill
Default Risk Spread	Moody's Baa corporate bond yield minus Moody's Aaa corporate bond yield
Interest Rate Volatility	Standard deviation of monthly 3-month constant maturity Treasury rate over a 12-month period prior to bond transaction date
Unemployment Rate	Unemployment rate in percent
GDP	Real gross domestic product (in billions of Chained 2017 USD)

Various steps are undertaken to preprocess the combined dataset. We handle missing values by imputing data for up to one year, meaning that an existing value is perpetuated until a new value is recorded or 52 weeks have passed. The TRACE bond data includes manually reported information from broker-dealers, which can be prone to input errors, potentially leading to inaccurate results. Therefore, the yield spreads and REIT-level accounting data are winsorized at the 5% and 95% percentiles to prevent outliers from distorting the results (Gu et al., 2020). This process is conducted on a monthly basis to ensure that future data points or REITs not included in the sample at a specific time are not incorporated. Table 4.3 presents the summary statistics for our variables. It is noteworthy that the mean and standard deviations for *OI* and *PI* are relatively similar, however, *NPT* is on average negative and exhibits a high variability. This is in line with Figure 4.1.

Table 4.3 Descriptive Statistics

Variable	Unit	Mean	SD	Min	Max
OI	Integer	0.0637	0.0393	0	0.2410
PI	Integer	0.0656	0.0356	0	0.2474
NPT	Integer	-0.0390	0.3406	-1	1
Bond Yield Spread	Percentage	0.0139	0.0085	-0.0365	0.0587
Coupon Rate	Percentage	0.0386	0.0102	0.0170	0.0775
Bond Price	U.S.-Dollar	98.67	10.16	64.14	127.79
Volume	U.S.-Dollar	423,44	396,02	10,08	2,989,667
Time to Maturity	Months	93.54	81.29	2	359
Credit Rating	Percentage	0.6767	0.4677	0	1
Call Status	Percentage	0.9252	0.2631	0	1
Return	Percentage	0.0036	0.0754	-0.5274	0.5940
Market_Cap	Mil $ (log)	9.4894	0.9847	6.7476	11.7325
Leverage	Percentage	0.5379	0.1208	0.3615	0.9304
Dividends per Share	U.S.-Dollar	0.8123	0.6086	0	3
Funds From Operations	Integer	134.32	152.04	-477.75	839.70
Market-to-Book	Integer	2.5972	1.8179	0.4246	20.3505
VIX	Integer	19.08	6.89	10.07	58.08
Default Risk Spread	Percentage	0.0092	0.0021	0.0055	0.0170
IVOL	Percentage	0.0040	0.0043	0.0001	0.0157
S&P 500	Integer	3,660	988	1,173	5,621
Term Spread	Percentage	-0.0167	0.0307	-0.0662	0.0304
GDP	Integer	21,167	1,331	17,031	23,400
Unemployment Rate	Percentage	0.0465	0.0189	0.0340	0.1480
Bond Zero Trading Days	Percentage	0.5923	0.2057	0.2581	0.9677
Firm Zero Trading Days	Percentage	0.3499	0.0845	0.2333	0.9000
Bid-Ask Spread	Percentage	0.0083	0.0090	0.0006	0.0710
Similarity	Percentage	0.9751	0.0510	0.4008	0.9981
Readability	Integer	24.58	4.01	15.87	32.43
Long-term Debt	Integer	7,989	6,119	715	28,724

Note: This table presents the summary statistics for a sample of 64 equity REITs over the period of 2011 to 2024. Variable definitions are in Table 4.2.

Table 4.4 presents the pair-wise correlations for variables in our dataset. The *OI* and *NPT* are negatively correlated with bond yield spreads, whereas the *PI* is positively correlated.

Table 4.4 Pairwise Correlations

Variable	OI	PI	NPT
OI	1.000***	0.295***	0.632***
PI	0.295***	1.000***	-0.421***
NPT	0.632***	-0.421***	1.000***
Bond Variables			
Bond Yield Spread	-0.003	0.009	-0.017***
Coupon Rate	0.001	0.009	-0.018***
Bond Price	-0.021***	0.031***	-0.026***
Volume	0.042***	-0.029***	0.072***
Time to Maturity	0.044***	-0.018***	0.080***
Credit Rating	0.065***	0.066***	0.046***
Call Status	-0.083***	-0.130***	0.006
Liquidity Variables			
Bond Zero Trading Days	0.053***	0.122***	-0.002
Firm Zero Trading Days	0.030***	0.023***	0.012**
Bid-Ask Spread	0.023***	0.056***	0.010*
REIT-Specific Variables			
Market_Cap	0.165***	-0.137***	0.254***
Return	-0.020***	0.054***	-0.055***
FFO	0.087***	-0.178***	0.205***
Leverage	0.227***	0.040***	0.074***
Dividends per Share	0.198***	-0.009	0.133***
Market-to-Book	0.345***	0.071***	0.215***
Long-term Debt	0.105***	-0.221***	0.229***
Equity Market Variables			
S&P 500	-0.025***	0.110***	-0.111***
VIX	0.009	0.103***	-0.043***
Macroeconomic Variables			
Term Spread	-0.004	0.030***	-0.013**
Default Risk Spread	0.022***	-0.022***	0.058***
IVOL	0.027***	0.041***	0.004
Unemployment Rate	-0.046***	0.105***	-0.084***
GDP	-0.009	0.071***	-0.072***
Disclosure Variables			
Readability	0.013**	0.035***	-0.005
Similarity	-0.055***	0.022***	-0.047***

Note: This Table presents the pair-wise correlations between the tone measures and other variables for a sample of 64 equity REITs over the period of 2011 to 2024. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

To disaggregate our tone measures, we follow previous studies (see, e.g., Ling et al., 2014; Huang et al., 2014) and use an orthogonalization approach: We first regress each of the tone measures on firm fundamentals (*Equity Return, Market Cap, Leverage, Dividends per Share, FFO, Market-to-book*) and retain the fitted values. The fitted values represent the component of disclosure tone that can be explained with firm fundamentals ($Tone_{Fundamental}$). The residuals from this regression represent the component of disclosure tone that cannot be explained by REIT fundamentals ($Tone_{Non\text{-}Fundamental}$).

4.5 Methodology

To assess the two dimensions of non-linearity in the relationship of disclosure tone and REIT bond yield spread, we employ a combination of machine learning and conventional regression approaches. Previous studies provide evidence for a superior performance of machine learning algorithms over conventional regression methods due to their ability to address the non-linearity and non-stationary data properties (see, e.g., Jenett et al., 2026; Loo, 2020). However, a crucial limitation of these machine learning approaches is the lack of interpretability of statistical significance. Therefore, we combine both approaches to ensure ideal outputs and an enhancement over an isolated application of either method. In particular, we employ two-way fixed effects regression and XGBoost algorithm in combination with SHAP values and ALE plots.

4.5.1 Fixed Effects Regression

We employ a panel regression with time-fixed and property-type fixed effects to assess the predictive value of aggregated and disaggregated tone measures for REIT bond yield spreads. To address endogeneity concerns and focus on prediction, we use lagged tone variables in our analysis. Control variables are contemporaneous. Our model is shown in Equation 4.4.

$$\begin{aligned} r_{i,t}^{REIT} - r_{i,t}^{Treasury} = {} & c_0 + \beta_1 OI + \beta_2 PI + \beta_3 NPT + \sum_{i=1}^{6} \chi_i Bond\ Controls \\ & + \sum_{i=1}^{3} \chi_i Liquidity\ Controls + \sum_{i=1}^{7} \chi_i REIT\ Controls \\ & + \sum_{i=1}^{2} \chi_i Equity\ Market\ Controls + \sum_{i=1}^{5} \chi_i Macroeconomic\ Controls \\ & + \gamma_t^{Time} + \gamma_t^{Property\ Type} + \epsilon_{i,t}, \end{aligned} \tag{4.4}$$

where $r_{i,t}^{REIT} - r_{i,t}^{Treasury}$ is the monthly REIT bond yield spread as the difference between the monthly REIT bond yield of REIT i at time t and the U.S. Treasury yield with the same maturity i at time t. γ_t^{Time} are year-fixed effects, $\gamma_t^{Property\ Type}$ are property type-fixed effects and $\epsilon_{i,t}$ is the residual component (error term). Our analysis using the disaggregated tone measures is based on Equation 4.4, however, REIT fundamentals are accounted for in the fundamentals-based tone measures and are not included in the model.

4.5.2 eXtreme Gradient Boosting (XGBoost)

While fixed effects regression assumes a linear relationship between the independent and dependent variables, we hypothesize that the tone-yield relationship is quadratic. One approach to assess linearity of a relationship is the XGBoost algorithm, which is a tree-based ensemble learning method. The origin of XGBoost can be attributed to Chen and Guestrin (2016), who introduced this algorithm to address the bias-variance trade-off commonly encountered in single decision trees. XGBoost has since demonstrated strong performance in tackling complex issues such as classifications, pattern recognition, and regression-based tasks, often surpassing traditional methods and alternative machine learning approaches in the field of REITs (see, e.g., Jenett et al., 2026; Habbab et al., 2023).

Tree-based ensemble learning algorithms improve predictive accuracy by aggregating the outcomes of multiple individual decision trees rather than relying on a single one. The basic idea of ensemble learning is that multiple weak learners, in our case, single decision trees, can be combined to form one strong learner. In the case of XGBoost, this relationship can be expressed as:

$$h(y|x) = \sum_{i=1}^{M} u_m h_m(y|x), \tag{4.5}$$

where h denotes the strong learner, h_m are the weak learners, $u_m$are their respective weights, M is the number of single trees, x presents the full features space and y is the response variable. In boosting, weak learners h_m are trained sequentially, with every new model focusing on improving the errors made by the previous ones. Gradient boosting extends this principle by iteratively adding trees that minimize the model's loss function using gradient descent. Extreme Gradient Boosting is a computationally efficient and highly scalable version of gradient boosting. Compared with parametric or semi-parametric models, XGBoost is capable of identifying complex, non-linear relationships and higher-order interactions within large datasets. This significantly reduces the need for manual optimization. Moreover, it requires less manual optimization than traditional models.[4]

4.5.3 SHapley Additive exPlanations (SHAP) and Accumulated Local Effects (ALE)

However, XGBoost is often referred to as a "black box", because it is not readily apparent how the model learns the relationships between input and output data. An emerging

[4] For more information about tree-based methods, ensemble learning, and gradient boosting, see Hastie et al. (2009).

branch of research that focuses on making neural networks and other machine learning methods interpretable is called eXplainable Artificial Intelligence (XAI). It allows for a deeper and graphical understanding of features considered in the analysis. SHAP values, developed by Lundberg and Lee (2017) allow us to see which individual features impact the model's estimates the most and to further see their evolution over time (Jenett et al., 2026).

To further understand how a feature affects the model's predictions, one feature is varied while everything else is held constant, and the resulting change in the model's prediction is observed. The global model-agnostic method of ALE plots provides insights into how an independent variable influences the average prediction of the dependent variable across all its values in the dataset. A drawback of other commonly used methods, such as the SHAP values and Partial Dependency Plots (PDP) by Friedman (2001), is that they assume that variables are uncorrelated, which is rarely the case in real-world applications in finance and real estate. ALE plots, introduced by Apley and Zhu (2016), address this issue by allowing for correlated features. As a result, ALE plots offer a more robust approach to understanding the effects of features on predictions. They are also gaining increasing attention in the real estate literature, as evidenced by studies such as Krämer et al. (2023), Lorenz et al. (2023) and Jenett et al. (2026).

To derive ALE plots for our tone measures and dependent variable, the full range of each independent variable $x_r \in \mathbb{R}^{Nx1}$, is divided into K bins. Let $Z_{r,k}$ denote the $\frac{k}{K}$ quantile of the empirical distribution with $Z_{r,0}$ and $Z_{r,K}$ being the minimum and maximum values, respectively. The set $S_{r,k}$ contains all observations that fall within the left open interval from $Z_{r,k-1}$ to $Z_{r,k}$ with $n_{r,k}$ being the number of observations within that bin. We define $k(x_r)$ as an index that identifies the bin corresponding to a given value of x_r. Consequently, the uncentered accumulated local effect is then given by:

$$g_{ALE}(x_r) = \sum_{k=1}^{k(x_r)} n_{r,k}^{-1} \sum_{i \in S_{r,k}} \left[f\left(Z_{r,k}, X_{\setminus r,i}\right) - f(Z_{r,k-1}, X_{\setminus r,i}) \right], \tag{4.6}$$

where $x_{\setminus r} \in \mathbb{R}^{NxP-1}$ is the set of features without the feature r of P variables and $f(.)$ the network's prediction formula. The quantity in the squared brackets delineates the prediction of $f(.)$ when observation i is replaced with $Z_{r,k}$ in the minuend and the prediction with $Z_{r,k-1}$ instead of the true value i in the subtrahend. These differences are aggregated for all observations within each bin $S_{r,k}$. Since this computation is repeated across all bins k, $g_{ALE}(x_r)$ represents the sum of these local effects weighted by the

number of observations in each bin (Apley and Zhu, 2020). The centered ALE main effect has a zero mean with respect to the marginal distribution of x_r and can be written as:

$$\ominus_{ALE}(x_r) = g_{ALE}(x_r) - N^{-1}\sum_{i=1}^{N} g_{ALE}(x_{r,i}). \quad (4.7)$$

Centering the ALE functions ensures that the resulting plots are interpretable. Specifically, the ALE plot consistently illustrates the impact of a feature as a function of the average prediction of the neural network across the entire feature space. Examining these ALE plots allows us to detect any non-linear relationships between the independent variables and the predicted bond yield spread.

4.6 Results

4.6.1 First Dimension of Non-Linearity

While our independent variable of interest is net positive tone (*NPT*), we also present the results for positive or optimistic tone (*OI*) and negative or pessimistic tone (*PI*) to provide more context. The results of our fixed effects regression for REIT bond yield spread and the aggregated tone measures are presented in Table 4.5. The negative or pessimistic tone in REIT financial statements (*PI*) positively predicts the bond yield spread in the next month. Thus, a negative disclosure tone predicts higher cost of debt for REITs. The positive and net positive tone in REIT financial statements have a negative relationship with the bond yield spread in the next month, however, coefficients are only significant at the 5% level. Our findings for the aggregated tone measures are in line with previous studies (Cao et al., 2025; Jin et al., 2024; Liang et al., 2023; Consoli et al., 2021; Wang, 2020) that find negative disclosure tone to have the highest informative value for bond investors.

Our results for the control variables are in line with previous studies on, for example, the positive co-movement of REIT bond yields and stock returns (Alexander et al., 2000), implied stock market volatility (Collin-Dufresne et al., 2000), default risk captured by market capitalization (Becker and Ivashina, 2015), liquidity risk (Longstaff et al., 2005) as well as credit rating and time to maturity (Nayak, 2010). Please note, S&P 500, Term Spread and GDP were excluded from the fixed effects regression due to multicollinearity, i.e., VIF values exceeding the critical value of 10. To ensure that multicollinearity is not affecting standard errors, we also estimate the regressions without control variables while keeping the fixed effects. Our results remain robust.

We further validate our findings in Table 4.5 using XAI. Specifically, the SHAP values reported in Figure 4.3 in Appendix I illustrate the relative importance of the sentiment measures in explaining bond yield spreads. *OI, PI,* and *NPT* all rank among the twenty most important features. Their relative ranking is broadly consistent with the magnitude of the corresponding regression coefficients, with PI exhibiting the strongest economic relevance, in line with the fixed effects regression results. Overall, these findings suggest that the conclusions obtained from the regression analysis are also supported by the ML- and XAI-based approach, consistent with prior studies (Stang et al., 2024; Jenett et al., 2026) showing that traditional regression methods and explainable machine learning often yield comparable insights.

Table 4.5 Regression Results for Aggregated Tone Measures and Bond Yield Spread

	OI	**PI**	**NPT**
$Tone_{t-1}$	-0.0007** (0.0003)	0.0018*** (0.0006)	-0.0008** (0.0004)
Coupon Rate	0.0078*** (0.0001)	0.0078*** (0.0001)	0.0078*** (0.0001)
Bond Price	-0.0107*** (0.0002)	-0.0107*** (0.0002)	-0.0107*** (0.0002)
Volume	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0009*** (0.0001)
Time to Maturity	0.0015*** (0.0001)	0.0016*** (0.0001)	0.0015*** (0.0001)
Credit Rating	0.0011*** (0.0000)	0.0012*** (0.0000)	0.0012*** (0.0000)
Call Status	0.0016*** (0.0001)	0.0016*** (0.0001)	0.0015*** (0.0001)
Return	0.0038*** (0.0003)	0.0036*** (0.0003)	0.0039*** (0.0003)
Market_Cap	-0.0113*** (0.0002)	-0.0109*** (0.0002)	-0.0111*** (0.0002)
Leverage	0.0003** (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)
Dividends per Share	0.0008*** (0.0001)	0.0010*** (0.0001)	0.0010*** (0.0001)
FFO	-0.0008*** (0.0002)	-0.0009*** (0.0002)	-0.0010*** (0.0002)
Market-to-Book	-0.0031*** (0.0003)	-0.0029*** (0.0003)	-0.0028*** (0.0003)
VIX	0.0036*** (0.0002)	0.0036*** (0.0002)	0.0036*** (0.0002)
Default Risk Spread	0.0041*** (0.0002)	0.0042*** (0.0002)	0.0040*** (0.0002)
IVOL	-0.0007*** (0.0001)	-0.0007*** (0.0001)	-0.0007*** (0.0001)
Unemployment Rate	0.0011*** (0.0002)	0.0010*** (0.0002)	0.0011*** (0.0002)
Bond Zero Trading Days	-0.0027*** (0.0001)	-0.0025*** (0.0001)	-0.0026*** (0.0001)
Firm Zero Trading Days	-0.0009*** (0.0002)	-0.0007*** (0.0002)	-0.0008*** (0.0002)
Bid-Ask Spread	0.0016*** (0.0002)	0.0016*** (0.0002)	0.0015*** (0.0002)
Similarity	0.0006*** (0.0002)	0.0005** (0.0002)	0.0005** (0.0002)
Readbility	0.0020*** (0.0003)	0.0022*** (0.0003)	0.0021*** (0.0003)
Long-term Debt	0.0033*** (0.0002)	0.0029*** (0.0002)	0.0027*** (0.0002)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.5773	0.5717	0.5761
Observations	30,172	30,172	30,172

Note: This Table presents the FE regression results for the three tone measures and REIT bond yield spread. REIT bond yield spreads are in decimals (e.g., 0.012 = 1.2%). SE are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

As an additional robustness check, we conduct a subperiod analysis to examine whether our baseline results are primarily driven by the COVID-19 period. The results, reported in Tables 4.10 – 4.12 in Appendix II, show that the estimated effects are generally stronger during the pandemic and the period of the subsequent interest rate adjustment, while the signs of the coefficients remain unchanged. In addition, the figures 4.4 – 4.6 in Appendix

III illustrate further SHAP values, that show the feature importance across the various subperiods. The findings suggest that, although tone is not the primary driver of bond yield spreads, sentiment measures have a non-negligible influence across periods when compared relatively to other control variables.

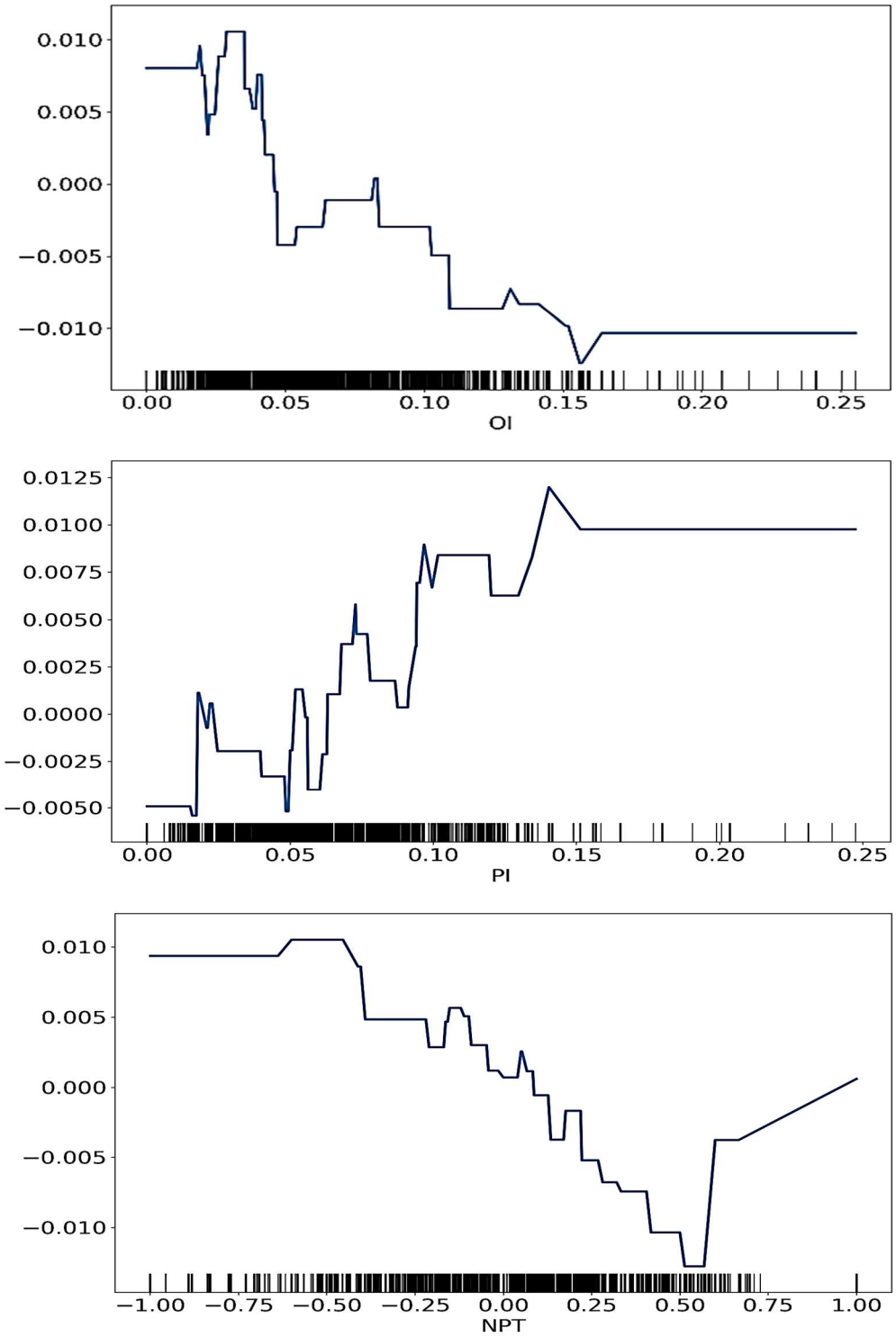
Next, we present the results of our investigation into whether the relationships of *OI, PI,* and *NPT* with bond yields spreads are linear or not using ALE plots derived from an XGBoost model. The ALE plots as shown in Figure 4.2 visualize how individual features influence the model's predictions beyond simple linear dependencies. Specifically, the ALE plots illustrate how changes in a feature's value impact the predicted bond yield spread, as shown by deviations from the average prediction along the y-axis for different values on the x-axis.

The ALE plots for the aggregative positive and negative tone measures (*OI* and *PI*) reveal non-linear patterns, suggesting that the impact of sentiment on REIT bond yield spreads is marked by reversals and saturation points rather than a consistent linear relationship. In particular, the ALE plot for *OI* shows a general negative relationship with bond yield spreads. However, this relationship flattens out at higher levels of optimism (around *OI* = 0.15), indicating a saturation point beyond which further increases in optimism no longer reduce the perceived credit risk. This finding suggests that while moderate optimism signals financial health and reduces borrowing costs, an overly positive disclosure tone may be viewed with suspicion by institutional bond investors, which is in line with previous studies on institutional investors in the stock market (Baginski et al., 2018; Blau, et al., 2015; Tan et al. 2014).

The effect of *PI* on bond yield spreads is positive. However, the relationship exhibits even more non-linearity than the *OI*-bond yield relationship. Initially, increases in pessimism sharply raise yield spreads, but this effect flattens beyond a threshold (around *PI* = 0.15). The diminishing marginal impact suggests that once a certain level of negative disclosure tone is reached, additional negativity does not substantially change investor perceptions of risk.

The ALE plot pattern for net positive tone measure (*NPT*) differs noticeably from *OI* and *PI*: At very negative tone levels (*NPT* between -1 and -0.5), the ALE plot shows a flat response in bond yield spreads, suggesting that a highly negative disclosure tone has a limited effect on bond yield spreads. As *NPT* increases from around -0.5 toward moderately positive values, yield spreads decline, consistent with the idea that a somewhat negative to neutral to somewhat positive tone signals lower risk. However, beyond the threshold of *NPT* > 0.5, the trend reverses. An overly positive tone is associated with increasing yield spreads.

Figure 4.2 ALE Plots for Tone Measures



While the ALE graphs for *OI* and *PI* suggest a somewhat linear relationship with the bond yield spread, the ALE graph for *NPT* suggests a quadratic relationship in which overly negative and positive disclosure tone increase the bond yield spread while mildly negative to neutral to mildly positive disclosure tone decreases it. Our findings for *NPT* are in line with our expectation that the tone-bond yield relationship is quadratic: A mildly

negative/neutral/mildly positive disclosure tone might signal a REIT's commitment to a high level of transparency and absence of tone management, which reduces the risk perception of bond investors and their required yield. However, a higher negative disclosure tone is likely to signal an increasing default risk to bond investors and increases their yield requirements. Similarly, a higher positive disclosure tone may signal higher risks considering that an overly positive disclosure tone has been found to negatively predict firm's financial performance (Jiang et al., 2019; Huang et al., 2014) as well as positively predict litigation risk (Rogers et al., 2011). Additionally, firms have been found to use a more positive disclosure language if they experience, for example, decreases in operating performance (Schleicher and Walker, 2010). Thus, an overly positive disclosure tone increases the risk perception of REIT bond investors and their required yield.

Considering our findings for NPT based on the ALE plots in Figure 4.2, we estimate our model in Equation 4.4 by including a quadratic term for *NPT*. Our results are presented in Table 4.6 and provide additional evidence for a quadratic relationship: While the coefficient on NPT is significantly negative, in line with Table 4.5, the coefficient on NPT^2 is significantly positive. For further robustness, we re-estimated the regression including a second and a third lag. The results for the quadratic terms stayed significant, showing persistent results.

Overall, our multi-methods approach using a combination of machine learning and conventional regression approaches suggest that the relationship between aggregated net positive tone and REIT bond yield spread is non-linear (quadratic) with overly negative and positive tone predicting a higher bond yields spread in the next month while a mildly negative to positive tone predict a lower spread.

Table 4.6 Regression Results for NPT and Bond Yield Spread

	Bond Yield Spread
NPT_{t-1}	-0.0009*** (0.0002)
NPT^2_{t-1}	0.0013*** (0.0002)
Coupon Rate	0.0078*** (0.0001)
Bond Price	-0.0107*** (0.0002)
Volume	-0.0009*** (0.0001)
Time to Maturity	0.0015*** (0.0001)
Credit Rating	0.0012*** (0.0000)
Call Status	0.0015*** (0.0001)
Return	0.0039*** (0.0003)
Market_Cap	-0.0111*** (0.0002)
Leverage	0.0002 (0.0001)
Dividends per Share	0.0010*** (0.0001)
FFO	-0.0010*** (0.0002)
Market-to-Book	-0.0028*** (0.0003)
VIX	0.0036*** (0.0002)
Default Risk Spread	0.0041*** (0.0002)
IVOL	-0.0007*** (0.0001)
Unemployment Rate	0.0011*** (0.0002)
Bond Zero Trading Days	-0.0026*** (0.0001)
Firm Zero Trading Days	-0.0009*** (0.0002)
Bid-Ask Spread	0.0015*** (0.0002)
Similarity	0.0005** (0.0002)
Readability	0.0021*** (0.0003)
Long-term Debt	0.0028*** (0.0002)
Time FE	Yes
Property Type FE	Yes
Adjusted R^2	0.5764
Observations	30,172

Note: This table presents the results of a two-way fixed effects regression for REIT bond yield spreads. NPT^2 is the quadratic term of the net positive tone measure (NPT). Standard errors are reported in brackets. Variables are defined in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

4.6.2 Second Dimension of Non-Linearity

Next, we present the results of our analysis of the disaggregated tone measures in Table 4.7. In line with our expectations, the fundamental and non-fundamental negative disclosure tone in REIT financial statements (*PI*) positively predict bond yield spread in the next month. Hereby, it is noteworthy that the coefficient on the non-fundamental tone component is larger than the fundamentals-based tone component. This is in line with our expectation that the information in the fundamentals-based negative tone component is not as novel to investors as it is captured in fundamental variables such as FFO, size, and growth opportunities. The negative tone not explained by firm fundamentals on the other hand has a higher informative value as it provides new information.

The fundamentals-based component of positive tone (*OI*) has no predictive power for bond yield spread while the non-fundamental component positively predicts it. Or put differently, an overly positive tone not explained by REIT fundamentals predicts a higher bond yield spread in the next month. This is in line with our expectation that the risk

perception of bond investors increases if a firm uses an overly positive tone and previous studies, which find that institutional investors penalize firms for using an overly positive tone in the stock market (Baginski et al., 2018; Blau et al., 2015; Tan et al., 2014).

Last, the fundamentals-based component of net positive tone (*NPT*) negatively predicts bond yield spread in the next month while the non-fundamental component positively predicts it. Thus, while an increase in the net positive tone based on REIT fundamentals reduces the bond yield spread in the next month, an increase in non-fundamental net positive tone increases it. The results for *OI* and *PI* in Table 4.7 suggest that the relationship of fundamentals-based net positive tone is driven by fundamental negative tone. On the other hand, the relationship of non-fundamental net positive tone and bond yield spread is driven by non-fundamental positive and negative tone.

Table 4.7 Regression Results for Disaggregated Tone Measures and Bond Yield Spread

	OI	PI	NPT
Fundamental Tone$_{t-1}$	-0.0042 (0.0031)	0.0074*** (0.0025)	-0.0024*** (0.0008)
Non-Fundamental Tone$_{t-1}$	0.0020*** (0.0005)	0.0094*** (0.0030)	0.0041*** (0.0013)
Coupon Rate	0.3942*** (0.0049)	0.3697*** (0.0048)	0.3395*** (0.0048)
Bond Price	-0.0005*** (0.0000)	-0.0005*** (0.0000)	-0.0004*** (0.0000)
Volume	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)
Time to Maturity	-0.0000*** (0.0000)	0.0000 (0.0000)	0.0000*** (0.0000)
Credit Rating	0.0018*** (0.0001)	0.0021*** (0.0001)	0.0018*** (0.0001)
Call Status	0.0047*** (0.0002)	0.0042*** (0.0002)	0.0040*** (0.0001)
VIX	0.0001*** (0.0000)	0.0001*** (0.0000)	0.0002*** (0.0000)
Default Risk Spread	0.5056*** (0.0409)	0.6190*** (0.0404)	0.6062*** (0.0395)
IVOL	-0.0885*** (0.0144)	-0.0793*** (0.0142)	-0.0817*** (0.0139)
Unemployment Rate	0.0437*** (0.0034)	0.0365*** (0.0033)	0.0302*** (0.0033)
Bond Zero Trading Days	-0.0064*** (0.0002)	-0.0071*** (0.0002)	-0.0079*** (0.0002)
Firm Zero Trading Days	0.0068*** (0.0005)	0.0040*** (0.0005)	0.0018*** (0.0005)
Bid-Ask Spread	0.0934*** (0.0049)	0.0794*** (0.0048)	0.0694*** (0.0047)
Similarity	0.0029*** (0.0011)	0.0010*** (0.0004)	0.0005*** (0.0008)
Readability	0.0004*** (0.0002)	0.0007*** (0.0003)	0.0001*** (0.0000)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.4935	0.5081	0.5298
Observations	30,172	30,172	30,172

Note: This Table presents the results of a two-way fixed effects regression of fundamental and non-fundamental tone measures and bond yield spread. Fundamental tone is the fitted value of the regression of the respective tone measure on the REIT fundamentals while non-fundamental tone is the residual. Variable descriptions are in Table 4.2. Standard errors are reported in brackets. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Overall, our results in Table 4.7 provide evidence for the presence of a second dimension of non-linearity in the tone-bond yield relationship when positive and negative disclosure tone are jointly accounted for (*NPT*). Additionally, they suggest that non-fundamental disclosure, irrespective of positive, negative or net positive, has a higher predictive value for REIT bond yield spreads than fundamentals-based tone. This is in line with our expectations that non-fundamental tone represents a new source of information to bond

investors signaling information about firm risks and improving the information environment around a REIT.

4.6.3 Robustness Checks

We conduct additional analyses to assess the robustness of our results. First, we derive our tone measures based on the entire financial statement as opposed to only the MD&A section. This robustness check accounts for the fact that REITs may disclose additional information in other parts of financial statements (e.g., risk factors, legal proceedings, regulatory disclosures). We estimate our model in Equation 4.4 for these alternative tone measures and present the results in Table 4.8. The results are in line with Table 4.5, with the exception of the coefficient of *OI*, which changes from significant at the 5% level to almost insignificant. This robustness check suggests they are robust to which textual sections in a REIT financial statement the tone measures are derived from.

Table 4.8 Robustness Check – Tone Measures Based on Entire Financial Statement

	OI	PI	NPT
Tonet-1	-0.0016* (0.0009)	0.0011*** (0.0003)	-0.0011** (0.0005)
Coupon Rate	0.0079*** (0.0001)	0.0078*** (0.0001)	0.0078*** (0.0001)
Bond Price	-0.0109*** (0.0002)	-0.0109*** (0.0002)	-0.0108*** (0.0002)
Volume	-0.0009*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Time to Maturity	0.0015*** (0.0001)	0.0015*** (0.0001)	0.0016*** (0.0001)
Credit Rating	0.0013*** (0.0000)	0.0013*** (0.0000)	0 .0013*** (0.0000)
Call Status	0.0015*** (0.0001)	0.0014*** (0.0001)	0.0014*** (0.0001)
Return	0.0036*** (0.0003)	0.0034*** (0.0003)	0.0035*** (0.0003)
Market_Cap	-0.0111*** (0.0002)	-0.0107*** (0.0002)	-0.0107*** (0.0002)
Leverage	-0.0000 (0.0001)	0.0002 (0.0001)	0.0003* (0.0001)
Dividends per Share	0.0009*** (0.0001)	0.0008*** (0.0001)	0.0009*** (0.0001)
FFO	-0.0012*** (0.0002)	-0.0010*** (0.0002)	-0.0014*** (0.0002)
Market-to-Book	-0.0033*** (0.0003)	-0.0032*** (0.0003)	-0.0031*** (0.0003)
VIX	0.0035*** (0.0002)	0.0036*** (0.0002)	0.0036*** (0.0002)
Default Risk Spread	0.0042*** (0.0002)	0.0043*** (0.0002)	0.0042*** (0.0002)
IVOL	-0.0008*** (0.0001)	-0.0008*** (0.0001)	-0.0007*** (0.0001)
Unemployment Rate	0.0012*** (0.0002)	0.0011*** (0.0002)	0.0012*** (0.0002)
Bond Zero Trading Days	-0.0024*** (0.0001)	-0.0024*** (0.0001)	-0.0024*** (0.0001)
Firm Zero Trading Days	-0.0010*** (0.0002)	-0.0010*** (0.0002)	-0.0010*** (0.0002)
Bid-Ask Spread	0.0016*** (0.0002)	0.0016*** (0.0002)	0.0016*** (0.0002)
Similarity	0.0005** (0.0002)	0.0005** (0.0002)	0.0005** (0.0002)
Readability	0.0014*** (0.0004)	0.0014*** (0.0004)	0.0014*** (0.0004)
Long-term Debt	0.0030*** (0.0002)	0.0029*** (0.0002)	0.0027*** (0.0002)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.5687	0.5677	0.5667
Observations	30,172	30,172	30,172

Note: This Table presents the fixed effects regression results for the three tone measures derived from the entire REIT financial statement and REIT bond yield spread. Standard errors are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Second, Wang (2020) shows that the response of investors in the CDS market to pessimistic tone in the MD&A section of financial statements is stronger for firms closer to default. Jin et al. (2024) find that the tone in financial statements has particularly strong predictive power for a firm's default risk if the firm is, amongst others, experiencing financial distress. As a consequence, we assess whether a higher default risk of a REIT, as proxied by a higher leverage and lower credit rating, further increases the predictive power of negative tone for future bond yield spread.

In particular, we create interaction effects of the tone measures and 1) leverage and 2) credit rating and the disclosure specific variables 3) similarity and 4) readability. We then estimate our model in Equation 4.4. Our results are presented in Table 4.9. The main effects and interaction term between *PI* and leverage are significantly positive. Thus, a more negative disclosure tone by higher leveraged REITs additionally increases the bond yield spread. This is in line with Jin et al. (2024) and Wang (2020), who find the informative value of disclosure tone to be particularly high for firms with higher financial challenges.

The interaction effect between *PI* and the credit rating dummy is significantly negative indicating that for investment-grade (non-investment grade) bonds, a negative tone in financial disclosures is associated with a decrease (increase) in bond yield spreads. On the other hand, the main and interaction effects for *OI* and *NPT* are insignificant or only significant at the 10% level. Overall, our results in Table 4.9 suggest that the informative value of negative disclosure tone in REIT financial statements for bond investors increases for REITs with a higher financial risk.

Last, we assess whether readability of and similarity between a firm's financial statements moderate the tone-bond yield relationship by creating interaction effects of our tone measures and similarity and readability respectively. For the disclosure variable similarity, the interaction effects are significant for the *OI* and the *PI* (Table 4.9). Positive repetitive disclosure might be interpreted as poor risk assessment while negative content that is highly repetitive may already be priced in by investors. As shown in Table 4.9, readability remains positive at the 5%- and 1%-level, irrespective of which tone measure is used. This indicates that more difficult to read disclosure results in higher bond yield spreads and is perceived as a risk.

Table 4.9 Robustness Check – Interaction Effects

	OI	PI	NPT
$Tone_{t-1}$	-0.0006* (0.0004)	0.0026*** (0.0002)	-0.0013* (0.0007)
*$Tone_{t-1}$ * $Leverage_{t-1}$*	0.0058 (0.0040)	0.0053*** (0.0008)	0.0088* (0.0050)
*$Tone_{t-1}$ * Credit Rating*	-0.0009* (0.0005)	-0.0008*** (0.0001)	-0.0000 (0.0002)
*$Tone_{t-1}$ * Similarity*	0.0011** (0.0005)	-0.0007*** (0.0001)	0.0013 (0.0018)
*$Tone_{t-1}$ * Readability*	0.0042*** (0.0003)	0.0017** (0.0008)	0.0080*** (0.0006)
Volume	0.0078*** (0.0001)	0.0079*** (0.0001)	0.0079*** (0.0001)
Bond Price	-0.0107*** (0.0002)	-0.0108*** (0.0002)	-0.0109*** (0.0002)
Coupon Rate	-0.0010*** (0.0001)	-0.0009*** (0.0001)	-0.0010*** (0.0001)
Time to Maturity	0.0015*** (0.0001)	0.0016*** (0.0001)	0.0015*** (0.0001)
Credit Rating	0.0008*** (0.0001)	0.0006*** (0.0001)	0.0012*** (0.0000)
Call Status	0.0015*** (0.0001)	0.0016*** (0.0001)	0.0014*** (0.0001)
Market Cap	0.0038*** (0.0003)	0.0036*** (0.0003)	0.0039*** (0.0003)
Dividends per Share	-0.0110*** (0.0002)	-0.0110*** (0.0002)	-0.0110*** (0.0002)
FFO	-0.0016*** (0.0002)	0.0011*** (0.0002)	-0.0000 (0.0001)
Equity Return	0.0008*** (0.0001)	0.0010*** (0.0001)	0.0010*** (0.0001)
$Leverage_{t-1}$	-0.0007*** (0.0002)	-0.0009*** (0.0002)	-0.0010*** (0.0002)
VIX	-0.0037*** (0.0003)	-0.0024*** (0.0003)	-0.0032*** (0.0003)
Market-to-Book	0.0036*** (0.0002)	0.0036*** (0.0002)	0.0036*** (0.0002)
Default Risk Spread	0.0041*** (0.0002)	0.0042*** (0.0002)	0.0040*** (0.0002)
IVOL	-0.0007*** (0.0001)	-0.0007*** (0.0001)	-0.0008*** (0.0001)
Unemployment Rate	0.0012*** (0.0002)	0.0010*** (0.0002)	0.0011*** (0.0002)
Bond Zero Trading Days	-0.0026*** (0.0001)	-0.0025*** (0.0001)	-0.0025*** (0.0001)
Firm Zero Trading Days	-0.0010*** (0.0002)	-0.0006*** (0.0002)	-0.0009*** (0.0002)
Bid-Ask Spread	0.0016*** (0.0002)	0.0016*** (0.0002)	0.0016*** (0.0002)
Similarity	0.0009*** (0.0003)	0.0006*** (0.0002)	0.0005** (0.0002)
Readability	0.0023*** (0.0006)	0.0022** (0.0009)	0.0022*** (0.0003)
Long-term Debt	0.0029*** (0.0002)	0.0029*** (0.0002)	0.0026*** (0.0002)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.5818	0.5738	0.5823
Observations	30,172	30,172	30,172

Note: This Table presents the fixed effects regression results for the three tone measures, its interaction effects with leverage, credit rating, readability, and similarity and REIT bond yield spread. Standard errors are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

4.7 Conclusion

The qualitative or soft information in corporate disclosures has been found to improve the information environment around firms for bond investors (Cao et al., 2025; Jin et al., 2024; Gupta et al., 2025; Lou, 2019). Hereby, not only what a firm discloses has informative value for bond investors, but also how it discloses information in terms of tone or readability. We use the findings of previous studies on the relationship of tone and bond yields (Schmeling and Wagner, 2025; Hirsch et al., 2024; Wang, 2020) as a starting point and investigate whether the assumption made by these studies about the linearity of this relationship is appropriate.

We hypothesize that two dimensions of non-linearity exist in the tone-bond yield relationship: First, we expect net positive tone, which jointly considers negative and positive tone in corporate disclosures, to have a quadratic relationship with the bond yield

spread. While a mildly negative or neutral tone may signal information about a firm's disclosure practices and credibility to investors, which reduces their risk perception and yield requirements, a higher positive or negative tone signals higher risks that impact a firm's default risk and results in higher bond investor risk perception and yield requirements.

Second, we disaggregate tone into a component that can be explained with firm characteristics and a non-fundamental component. We hypothesize that these components of net positive tone impact bond yield spreads differently. While we expect the fundamentals-based tone to have a negative relationship with bond yield spread, we expect the non-fundamental tone to have a positive relationship one. Additionally, the non-fundamental tone is expected to have a higher predictive value for bond yield spread as it contains new information for bond investors.

In our empirical analysis, we use equity REITs as a laboratory and apply a multi-method approach. In particular, we use a large language model (RoBERTa) to extract tone measures from the financial statements of 64 bond-issuing REITs over the period of 2011 to 2024 and employ an XGBoost algorithm in combination with ALE plots to assess the linearity of the tone-bond yield relationship. We also use conventional fixed effects regression to assess the relationships of aggregated and disaggregated tone measures with REIT bond yields.

Our results provide evidence for the two dimensions of non-linearity in the tone-yield relationship. We firstly show that net positive tone has a quadratic relationship with REIT bond yield spread in the next month. We secondly find the fundamental and non-fundamental net positive tone to predict the future REIT bond yield spread in different directions. While fundamentals-based net positive tone negatively predicts the REIT bond yield, the non-fundamental net positive tone positively predicts it. Our results suggest that the non-fundamental component of disclosure tone has a higher informative value to bond investors than the fundamentals-based component. Overall, our results suggest that the relationship of disclosure tone and bond yield is more complex than assumed in previous studies, and future investigations need to account for aspects of non-linearity identified in this study.

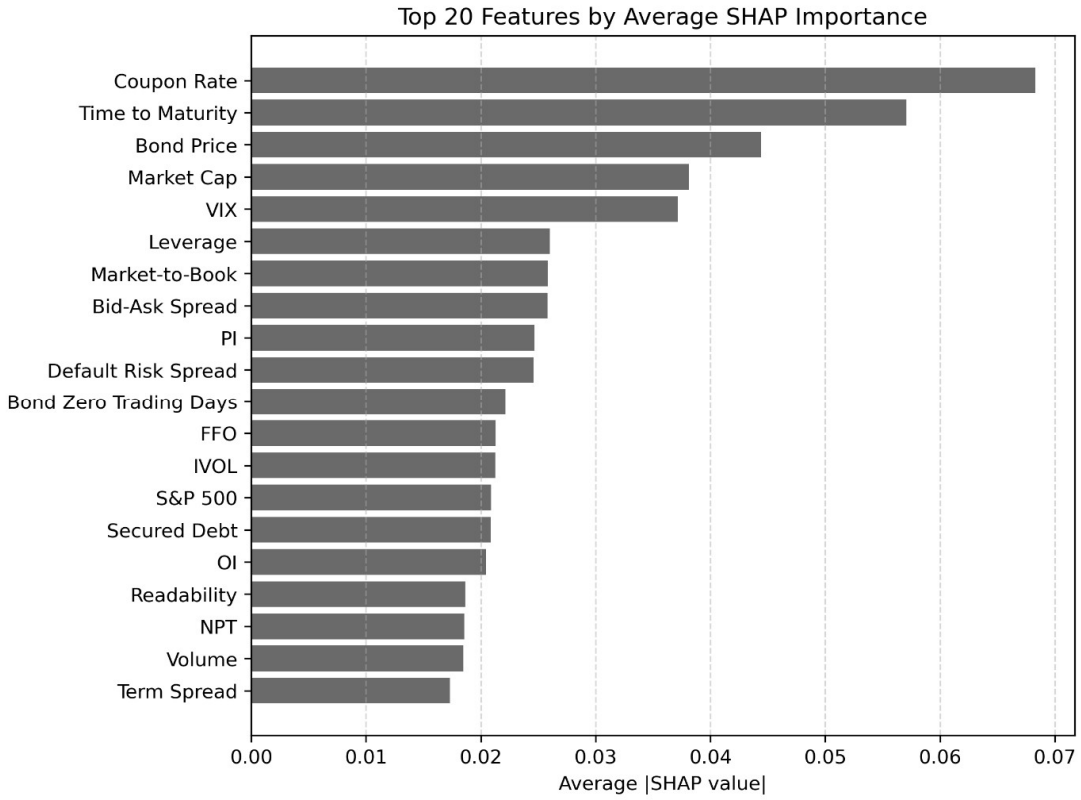
Practical implications arise for both REIT managers and bond investors. Managers should avoid overly positive or negative tone and ensure alignment with fundamentals to limit financing costs. For investors, disclosure tone, especially its non-fundamental component, provides useful additional signals for predicting bond yield spreads.

Future study may use our findings as a starting point to investigate the relationship of disclosure tone and bond yields. While we lack the access to the respective data about secured debt by REITs, future studies may investigate whether the tone-bond yield relationship varies across REITs with different debt capital structures in terms of secured and unsecured long-term debt. Additionally, future studies may further investigate strategic tone management in corporate disclosures by REITs or analyze the informative value of non-fundamentals-based disclosure tone for investor decision-making in more detail. Lastly, future studies may investigate whether the response to tone varies by investor type or how large institutional investors impact the tone-yield relationship.

4.8 Appendix

4.8.1 Appendix I

Figure 4.3 SHAP Values for feature importance



4.8.2 Appendix II

Table 4.10 Regression Results for Aggregated Tone Measures and Bond Yield Spread (2011 – 2019)

	OI	PI	NPT
Tone$_{t-1}$	-0.0010*** (0.0001)	0.0009*** (0.0002)	-0.0008*** (0.0001)
Coupon Rate	0.0064*** (0.0002)	0.0063*** (0.0002)	0.0065*** (0.0002)
Bond Price	-0.0075*** (0.0004)	-0.0076*** (0.0004)	-0.0075*** (0.0004)
Volume	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Time to Maturity	0.0015*** (0.0001)	0.0016*** (0.0001)	0.0014*** (0.0001)
Credit Rating	0.0010*** (0.0000)	0.0010*** (0.0000)	0.0011*** (0.0000)
Call Status	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0005*** (0.0001)
Return	0.0039*** (0.0004)	0.0039*** (0.0004)	0.0039*** (0.0004)
Market_Cap	-0.0071*** (0.0003)	-0.0069*** (0.0003)	-0.0069*** (0.0003)
Leverage	0.0011*** (0.0002)	0.0016*** (0.0002)	0.0013*** (0.0002)
Dividends per Share	0.0010*** (0.0002)	0.0013*** (0.0002)	0.0011*** (0.0002)
FFO	-0.0010*** (0.0003)	-0.0013*** (0.0003)	-0.0014*** (0.0003)
Market-to-Book	-0.0060*** (0.0005)	-0.0060*** (0.0005)	-0.0055*** (0.0005)
VIX	0.0043*** (0.0003)	0.0043*** (0.0003)	0.0043*** (0.0003)
Default Risk Spread	0.0036*** (0.0002)	0.0036*** (0.0002)	0.0036*** (0.0002)
IVOL	-0.0005 (0.0006)	-0.0005 (0.0006)	-0.0003 (0.0006)
Unemployment Rate	0.0069*** (0.0013)	0.0070*** (0.0013)	0.0069*** (0.0013)
Bond Zero Trading Days	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)
Firm Zero Trading Days	0.0008*** (0.0002)	0.0009*** (0.0002)	0.0008*** (0.0002)
Bid-Ask Spread	0.0017*** (0.0002)	0.0018*** (0.0002)	0.0017*** (0.0002)
Similarity	0.0005** (0.0002)	0.0006*** (0.0002)	0.0005*** (0.0002)
Readability	0.0009*** (0.0002)	0.0009*** (0.0002)	0.0010*** (0.0002)
Long-term Debt	0.0025*** (0.0003)	0.0025*** (0.0003)	0.0023*** (0.0003)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.5992	0.5981	0.5991
Observations	30,172	30,172	30,172

*Note: This Table presents the fixed effects regression results for the three tone measures and REIT bond yield spread. REIT bond yield spreads are in decimals (e.g., 0.012 = 1.2%). Standard errors are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.*

Table 4.11 Regression Results for Aggregated Tone Measures and Bond Yield Spread (2020 – 2021)

	OI	PI	NPT
Tone$_{t-1}$	-0.0036*** (0.0003)	0.0012*** (0.0002)	-0.0016*** (0.0002)
Coupon Rate	0.0128*** (0.0003)	0.0128*** (0.0004)	0.0127*** (0.0004)
Bond Price	-0.0130*** (0.0005)	-0.0129*** (0.0005)	-0.0129*** (0.0005)
Volume	-0.0011*** (0.0003)	-0.0010*** (0.0003)	-0.0011*** (0.0003)
Time to Maturity	0.0027*** (0.0002)	0.0027*** (0.0002)	0.0027*** (0.0002)
Credit Rating	0.0020*** (0.0001)	0.0021*** (0.0001)	0.0021*** (0.0001)
Call Status	0.0023*** (0.0001)	0.0023*** (0.0001)	0.0020*** (0.0001)
Return	0.0040*** (0.0004)	0.0038*** (0.0004)	0.0041*** (0.0004)
Market_Cap	-0.0102*** (0.0005)	-0.0098*** (0.0005)	-0.0099*** (0.0005)
Leverage	-0.0013*** (0.0003)	-0.0007** (0.0003)	-0.0007** (0.0003)
Dividends per Share	0.0002 (0.0002)	0.0002 (0.0002)	0.0004* (0.0002)
FFO	-0.0001 (0.0003)	0.0003 (0.0003)	-0.0002 (0.0003)
Market-to-Book	0.0003 (0.0005)	0.0008 (0.0006)	0.0006 (0.0006)
VIX	0.0025*** (0.0005)	0.0017*** (0.0005)	0.0022*** (0.0005)
Default Risk Spread	0.0090*** (0.0009)	0.0110*** (0.0009)	0.0098*** (0.0009)
IVOL	0.0002 (0.0006)	0.0003 (0.0007)	0.0008 (0.0007)
Unemployment Rate	-0.0015*** (0.0005)	-0.0026*** (0.0005)	-0.0021*** (0.0005)
Bond Zero Trading Days	-0.0020*** (0.0001)	-0.0018*** (0.0001)	-0.0019*** (0.0001)
Firm Zero Trading Days	-0.0038*** (0.0005)	-0.0039*** (0.0005)	-0.0043*** (0.0005)
Bid-Ask Spread	0.0002 (0.0003)	0.0001 (0.0003)	0.0000 (0.0003)
Similarity	-0.0019* (0.0010)	-0.0027*** (0.0010)	-0.0030*** (0.0010)
Readability	-0.0022*** (0.0005)	-0.0028*** (0.0005)	-0.0023*** (0.0005)
Long-term Debt	0.0026*** (0.0004)	0.0023*** (0.0004)	0.0017*** (0.0004)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.6722	0.6646	0.6657
Observations	30,172	30,172	30,172

Note: This Table presents the fixed effects regression results for the three tone measures and REIT bond yield spread. REIT bond yield spreads are in decimals (e.g., 0.012 = 1.2%). Standard errors are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 4.12 Regression Results for Aggregated Tone Measures and Bond Yield Spread (2022 – 2024)

	OI	PI	NPT
$Tone_{t-1}$	-0.0022*** (0.0002)	0.0006*** (0.0002)	-0.0024*** (0.0002)
Coupon Rate	0.0095*** (0.0003)	0.0093*** (0.0003)	0.0094*** (0.0003)
Bond Price	-0.0181*** (0.0004)	-0.0179*** (0.0004)	-0.0180*** (0.0004)
Volume	-0.0004 (0.0003)	-0.0003 (0.0003)	-0.0003 (0.0003)
Time to Maturity	-0.0018*** (0.0002)	-0.0017*** (0.0002)	-0.0017*** (0.0002)
Credit Rating	0.0005*** (0.0001)	0.0006*** (0.0001)	0.0005*** (0.0001)
Call Status	0.0021*** (0.0001)	0.0020*** (0.0001)	0.0020*** (0.0001)
Return	0.0046*** (0.0004)	0.0044*** (0.0004)	0.0047*** (0.0004)
Market_Cap	-0.0112*** (0.0004)	-0.0110*** (0.0004)	-0.0112*** (0.0004)
Leverage	-0.0006*** (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
Dividends per Share	0.0010*** (0.0002)	0.0012*** (0.0002)	0.0013*** (0.0002)
FFO	0.0004 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)
Market-to-Book	-0.0023*** (0.0005)	-0.0024*** (0.0005)	-0.0024*** (0.0005)
VIX	-0.0036*** (0.0006)	-0.0035*** (0.0006)	-0.0035*** (0.0006)
Default Risk Spread	-0.0030*** (0.0006)	-0.0033*** (0.0006)	-0.0033*** (0.0006)
IVOL	-0.0003* (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Unemployment Rate	-0.0396*** (0.0028)	-0.0414*** (0.0028)	-0.0399*** (0.0028)
Bond Zero Trading Days	-0.0034*** (0.0001)	-0.0033*** (0.0001)	-0.0034*** (0.0001)
Firm Zero Trading Days	-0.0035*** (0.0005)	-0.0037*** (0.0005)	-0.0037*** (0.0005)
Bid-Ask Spread	0.0016*** (0.0003)	0.0015*** (0.0003)	0.0016*** (0.0003)
Similarity	0.0016*** (0.0004)	0.0015*** (0.0004)	0.0019*** (0.0004)
Readability	0.0013*** (0.0003)	0.0013*** (0.0003)	0.0012*** (0.0003)
Long-term Debt	0.0028*** (0.0002)	0.0024*** (0.0003)	0.0023*** (0.0002)
Time FE	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes
Adjusted R^2	0.5861	0.5817	0.5872
Observations	30,172	30,172	30,172

Note: This Table presents the fixed effects regression results for the three tone measures and REIT bond yield spread. REIT bond yield spreads are in decimals (e.g., 0.012 = 1.2%). Standard errors are reported in brackets. Variable definitions are in Table 4.2. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

4.8.3 Appendix III

Figure 4.4 SHAP Values for Feature Importance (2016-2019)

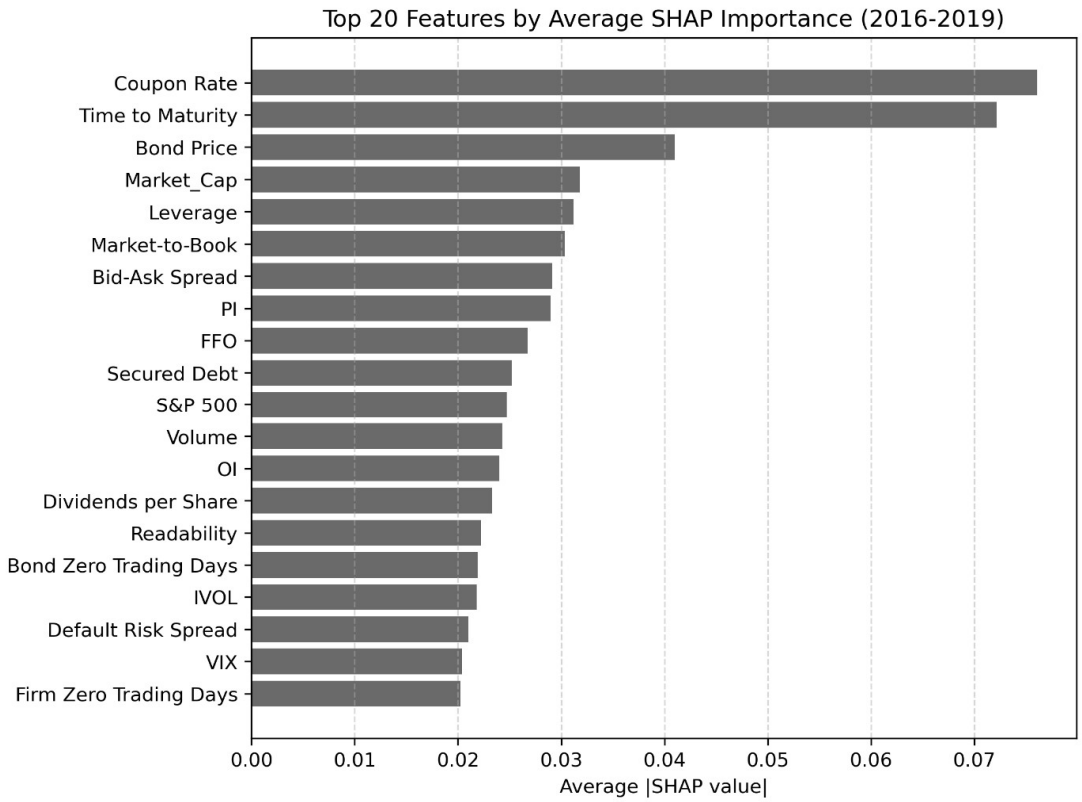


Figure 4.5 SHAP Values for Feature Importance (2020-2021)

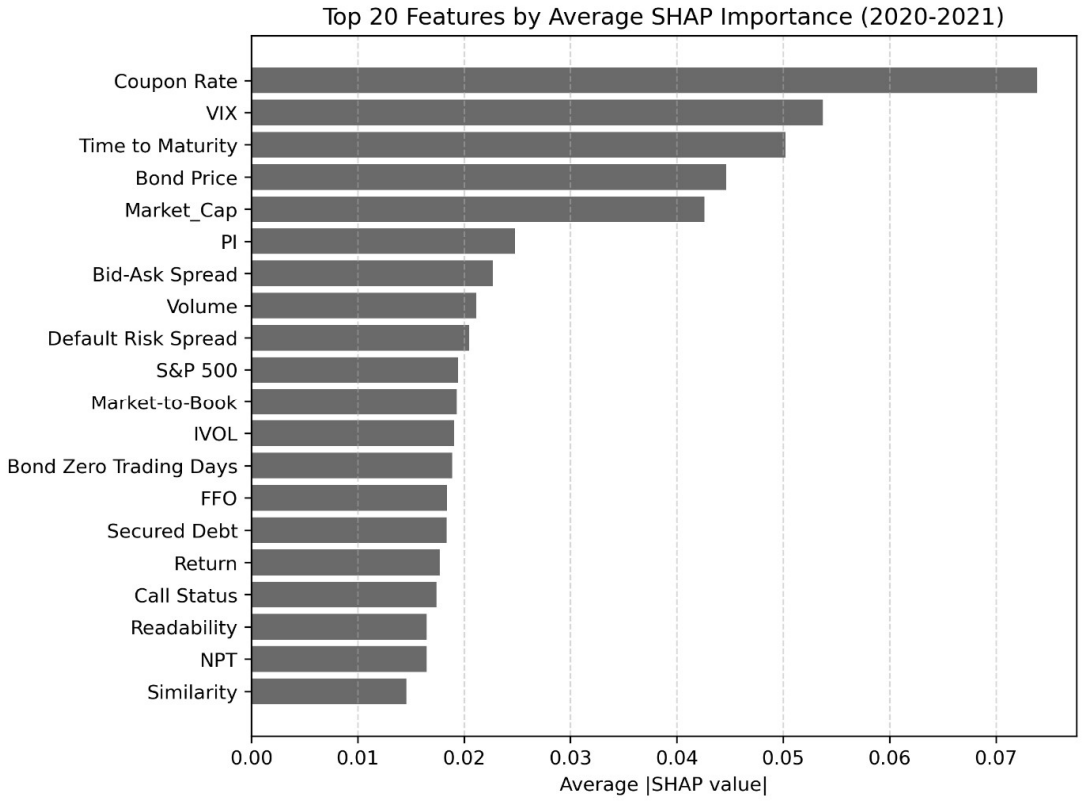
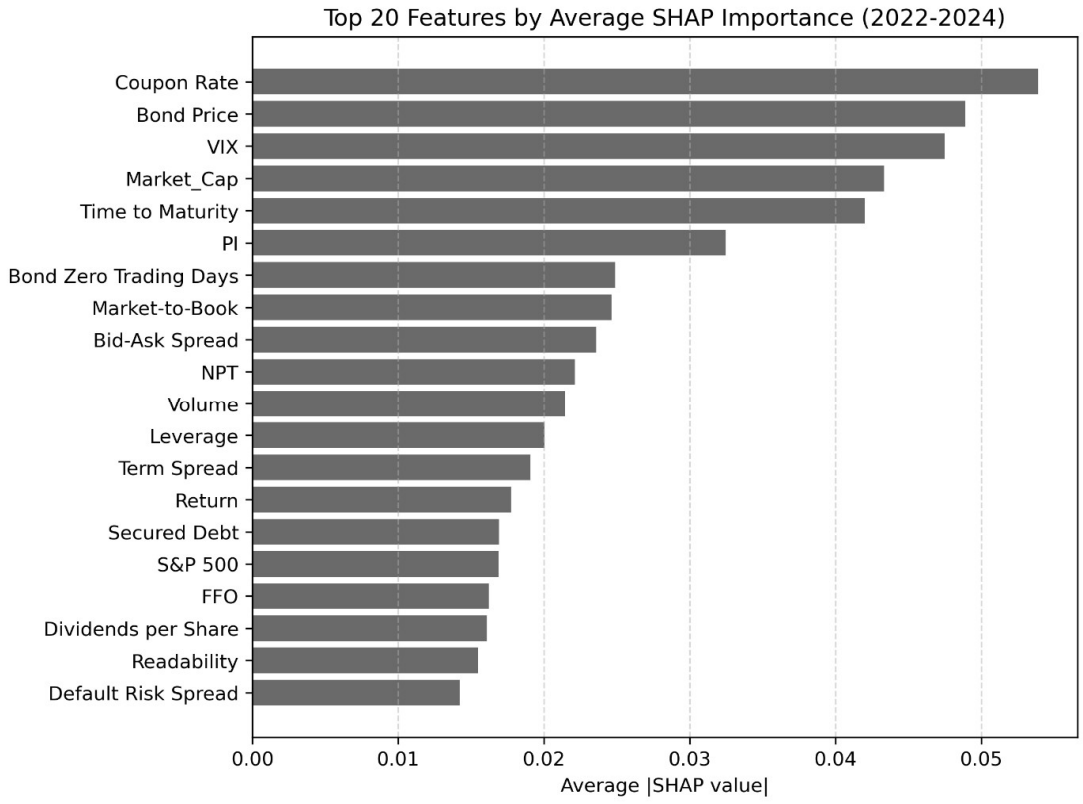


Figure 4.6 SHAP Values for Feature Importance (2022-2024)



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5 Conclusion

5.1 Executive Summary

This section briefly summarizes the three research studies that are included in the cumulative dissertation. For each study, the research objective and questions, as well as the data and methodology used, are explained. Finally, the most relevant findings and their implications for science and practice are presented.

Paper 1: Fundamentals or Noise? The Informative Value of Twitter Sentiment for REIT Returns

Problem and Objective

While previous sentiment-related research mainly focused on investor sentiment derived from surveys, news, or corporate disclosures, Twitter sentiment analysis shifts the focus to a broader investor base represented on social media (e.g., Ammari et al., 2023; Paulus et al., 2025). However, previous research has not fully explained why aggregated sentiment on social media channels is informative for stock returns, trading volume, and liquidity. There is limited understanding of whether this informative value reflects rational, fundamentals-based information or irrationality and noise.

Social media, and Twitter in particular, became especially popular during the COVID-19 pandemic, alongside trading platforms such as Robinhood that are primarily targeted at individual investors (Ozik et al., 2021). These individual investors, who are broadly represented on social media, tend to gravitate toward attention-grabbing stocks (Barber and Odean, 2008). The Real Estate Investment Trust (REIT) market provides a suitable setting because REITs are normally less familiar and less consumer-oriented than typical attention-grabbing stocks, while COVID suddenly increased public attention to commercial real estate sectors such as office, retail, logistics, and hospitality as they were heavily affected by restrictions.

Therefore, the objective of this paper is to examine whether the informative value of REIT-specific Twitter sentiment for REIT returns changed during the COVID-19 pandemic. Additionally, the paper questions whether the REIT return-sentiment relationship is driven by rational, fundamentals-based sentiment or by non-fundamental-based sentiment. To address this, the study uses three sentiment measures and decomposes Twitter sentiment

into rational and irrational components, building on the assumption that stay-at-home orders and easier access to commission-free trading increased retail investors' engagement with financial markets and potentially their exposure to REIT-related information.

Methodology and Data

The initial sample for this study comprises over 3.9 million tweets from the period 2014–2022. The tweets are collected with firm identifiers of U.S. REITs via the Tweepy API and pre-processed using Twitter-related techniques, including converting to lowercase, accounting for slang, and removing stop words (Manning et al., 2008; Paulus et al., 2025). The sample period is split into the pre-COVID period from January 2014 to January 2020 and the COVID period from February 2020 to December 2022. The time span ist limited because Twitter as a social media channel was not used extensively before 2014 and at the beginning of 2023 the platform was rebranded to X, resulting in significant API restrictions. The study includes macroeconomics (e.g. inflation, unemployment rate), capital (e.g. stock market sentiment, volatility) and real estate market (e.g. repeated sales index) variables. These variables are first used to assess the extent to which Twitter sentiment reflects macroeconomic, capital market, and real estate market fundamentals.

To ensure the relevance of the tweets and filter out messages related to cryptocurrency or other digital asset-related content, a Global Vector (GloVe)-based machine learning algorithm is applied (Paulus et al., 2025). After extensive filtering, including the removal of duplicates and irrelevant cryptocurrency-related content, the final sample consists of 175,130 REIT-relevant tweets. From these tweets, monthly Optimism, Pessimism, and Sentiment Quotient measures are constructed. Sentiment classification is performed using RoBERTa (Liu et al., 2019), which is optimized and pre-trained for Twitter sentiment analysis.

In the first empirical step, the sentiment measures serve as dependent variables in Autoregressive Distributed Lag (ARDL) models that explain sentiment through fundamentals. Then, an orthogonalization approach based on Ling et al. (2014) is used to extract the rational and irrational components of sentiment. In the second empirical step, REIT total returns are modeled in a Vector Autoregressive with Exogenous Variables (VARX) framework using the rational and irrational sentiment components.

Results and their Contribution to Science and Practice

The core finding of the study is that, when disaggregated, the relationship between Twitter sentiment and REIT returns differs across the two subperiods. While fundamentals-based sentiment is stronger during the pandemic, irrational sentiment is stronger before the

pandemic, when investors were potentially less engaged with market and firm-level information. Pessimistic sentiment has the highest explanatory power for REIT returns.

The paper contributes to the literature on individual investor sentiment in real estate by using Twitter sentiment as a proxy for individual REIT investor sentiment. By splitting sentiment into rational and irrational components, the study further improves the understanding of individual investor behavior during times of crisis. From a practical point of view, the results show that the sophistication of individual investors, as well as their ability to investigate markets, can change over time. For practitioners, the findings imply that REIT-related Twitter sentiment, especially pessimistic sentiment, can contain pricing-relevant information, but its interpretation depends on the market environment and on whether it reflects fundamentals or noise.

Paper 2: Signals or Stories? ESG Sentiment and Investor Reactions in REIT Corporate Disclosure

Problem and Objective

With the increasing relevance of the climate crisis and the growing importance of social issues such as diversity, equity, and inclusion, environmental, social, and governance (ESG) has become an important topic in academic research and investment practice (Robinson and McIntosh, 2022). REITs are particularly relevant in this context, as they link financial markets with underlying real estate assets, which account for a substantial share of greenhouse gas emissions. In addition, the social dimension of ESG has gained importance in recent years, while governance remains especially relevant for REIT investors due to the sector's specific regulatory structure and agency-related issues (Kohl and Schäfers, 2012; Robinson and McIntosh, 2022; Zheng and Lee, 2026).

Prior REIT research shows that the tone of mandatory disclosure documents can affect stock market reactions around disclosure events (Doran et al., 2012; Koelbl, 2020; Carstens and Freybote, 2021). However, the role of ESG-related sentiment in REIT disclosures remains underexplored. Existing ESG-performance studies mostly rely on quantitative ESG scores or ratings, while textual ESG sentiment has rarely been analyzed directly. Moreover, aggregate ESG measures may obscure value-relevant differences between individual pillars and property types (Liang et al., 2021; Erol et al., 2023; Fan et al., 2024; Zheng and Lee, 2026; Han et al., 2025).

Therefore, this study aims to develop an ESG-focused sentiment extraction approach for REIT corporate disclosure documents, including 10-K filings, 10-Q filings, and voluntary ESG reports. Based on these documents, the study constructs firm-level ESG sentiment measures per disclosure event and examines their relation to cumulative abnormal returns (CARs) in an event study framework around disclosure dates. The main objective is to analyze whether investors respond to ESG-related sentiment in REIT disclosures and whether this response differs across ESG pillars, disclosure channels, and REIT property types.

Methodology and Data

The analysis is based on publicly traded U.S. equity REITs that were constituents of the NAREIT index at any time between 2016 and 2025. The dataset consists of textual disclosure documents, including approximately 1,500 Form 10-K filings, 3,600 Form 10-Q filings collected from EDGAR, and around 400 voluntary ESG reports gathered from

company websites. In addition, macroeconomic, financial market, and firm-level data are used to compute abnormal returns and control variables.

To identify ESG-related text segments within the reports, the study applies a fine-tuned ESG-Robustly optimized BERT approach (RoBERTa) model, which classifies paragraphs into the three ESG pillars: environmental, social, and governance (Schimanski et al., 2024). The identified ESG paragraphs are then classified into positive, negative, and neutral sentiment categories using another fine-tuned RoBERTa-based sentiment model trained on financial text data (Malo et al., 2014). Based on these classifications, a Net Positive Tone (NPT) measure is constructed, defined as the difference between positive and negative ESG-related paragraphs scaled by the total number of paragraphs.

The empirical analysis follows an event study design. Daily stock returns are used to calculate abnormal returns based on a historical mean-adjusted return model, using an estimation window before the disclosure event. Cumulative Abnormal Returns (CARs) are then computed over several event windows, namely [–1,1], [–3,3], [–5,5], and [–1,10], to capture market reactions. For 10-K and 10-Q filings, the event dates are based on EDGAR timestamps, while for ESG reports, the publication dates are taken from press releases on company websites.

Multiple variations of the Ordinary Least Squares (OLS) regression model are calculated to cover the different pillars of ESG and the different asset classes in the REIT universe individually. Time-fixed effects are applied to control for external shocks like the COVID-19 pandemic, wars and interest rate changes.

Results and their Contribution to Science and Practice

The study shows that ESG sentiment in REIT disclosures is not priced uniformly by investors. Aggregate ESG sentiment has only limited explanatory power for CARs, suggesting that investors do not respond to ESG language as a single homogeneous signal. Instead, the results become more informative when ESG sentiment is analyzed separately by disclosure channel, ESG pillar, and REIT property type. At the pillar level, however, the findings show more differentiated effects. Environmental sentiment in mandatory filings emerges as the most stable and significant driver of CARs across several event windows. Social sentiment shows weaker and more context-dependent effects, while governance sentiment is largely insignificant. The analysis of voluntary ESG reports shows a different pattern. Overall sentiment in these reports is not significantly associated with CARs. At the pillar level, environmental and governance sentiment remain largely insignificant, while social sentiment is associated with negative market reactions in one event window. The results also differ across REIT property types. Environmental sentiment is particularly relevant in

operationally intensive asset classes such as industrial, lodging, and health care REITs, where energy efficiency, operating expenses, retrofit needs, and regulatory exposure are closely linked to asset performance. Social sentiment is less consistent but appears more relevant in sectors with higher levels of human interaction, such as lodging. Governance sentiment remains mostly insignificant, although some property-type-specific effects appear for residential and retail REITs.

The paper contributes to the ESG disclosure and sentiment literature by showing that ESG-related textual sentiment in REIT disclosures is processed selectively rather than uniformly by investors. It also adds evidence that ESG communication is more value-relevant when it is analyzed at the level of individual pillars, disclosure channels, and asset classes rather than as an aggregate ESG signal. The contribution to the practice is REIT managers should not rely on generically positive ESG language. Instead, ESG communication should be credible, specific, financially grounded, and closely aligned with the underlying property portfolio.

Paper 3: The Non-Linear Dynamics of Disclosure Tone and REIT Bond Yields

Problem and Objective

Corporate disclosure tone does not only affect REIT equity markets, but also REIT debt markets. Prior research shows that disclosure tone predicts firms' default risk and influences bond investor behavior (Jin et al., 2024; Cao et al., 2025). However, existing studies mainly rely on aggregated sentiment measures and assume a linear relationship between tone and bond market outcomes. This linearity assumption may not adequately capture the way bond investors interpret disclosure tone, especially when tone becomes overly positive or overly negative. This study examines two dimensions of non-linearity in the relationship between REIT disclosure tone and bond yield spreads. First, investors may interpret tone differently once it passes a certain threshold. Overly positive tone has been shown to negatively predict financial performance (Huang et al., 2014; Jiang et al., 2019), while overly negative tone may be penalized by investors (Tan et al., 2014; Blau et al., 2015; Baginski et al., 2018). Second, the study separates disclosure tone into a fundamentals-based and a non-fundamental component.

The aim of the study is to analyze the dynamic relationship between REIT disclosure tone and REIT bond yield spreads as a measure of credit risk. In doing so, it differentiates between fundamental and non-fundamental sentiment and tests the robustness of the results across different risk, disclosure, and macroeconomic settings.

Methodology and Data

The sample consists of 30,172 observations in total. Monthly bond yield spreads from 64 bond-issuing U.S. equity REITs between 2011 and 2024 are the main variable. The textual data is derived from Form 10-K and 10-Q filings obtained from EDGAR. The main analysis focuses on the Management Discussion and Analysis (MD&A) sections of these filings, while the full financial statements are used as a robustness check. Disclosure tone is classified using a fine-tuned RoBERTa model trained on the SEntFiN dataset (Sinha et al., 2022). The study uses NPT, which captures the balance between positive and negative language, as the main sentiment measure. In addition, the analysis includes a broad set of disclosure, bond, liquidity, accounting, and macroeconomic control variables.

Methodologically, the study first calculates the sentiment measures and then separates them into fundamentals-based and non-fundamental components using an orthogonalization approach following Ling et al. (2014). The fundamentals-based component is represented by the fitted values from a regression of tone on firm

fundamentals, while the residuals represent the non-fundamental component. The empirical approach combines traditional fixed effects regression with machine learning methods. An eXtreme Gradient Boosting (XGBoost) model is used to detect non-linear patterns in the tone-spread relationship. To make the machine learning results interpretable, the study applies Accumulated Local Effects (ALE) plots and SHapley Additive exPlanations (SHAP) values. The identified non-linearity is then tested in the fixed effects regression by including a quadratic NPT term.

Results and their Contribution to Science and Practice

The main results show that the relationship between disclosure tone and REIT bond yield spreads is non-linear in two dimensions. First, net positive tone has a quadratic relationship with future bond yield spreads. Mildly negative, neutral, or mildly positive tone is associated with lower spreads, while overly positive or overly negative tone signals higher risk and leads to higher bond risk premiums. This pattern is visible in the ALE plots and is confirmed in the fixed effects regression through a significant quadratic NPT term. Second, the distinction between fundamentals-based and non-fundamental tone provides additional insights. Fundamentals-based net positive tone negatively explains future bond yield spreads, while non-fundamental net positive tone positively adjusts them. This suggests that tone not explained by observable firm fundamentals contains additional information for bond investors. Overall, the results indicate that managerial tone in REIT financial disclosures contains more information for bond markets than previously assumed.

The study contributes to the literature by challenging the common assumption of a linear tone-yield relationship in bond markets. It also extends the research on REIT bonds. The findings suggest that REIT managers should avoid overly positive or overly negative disclosure tone and align their reporting language closely with firm fundamentals.

5.2 Final Remarks

While Artificial Intelligence and digital processes are getting increasingly relevant in different tasks and workstreams, the human element is still present in decision-making. Financial markets are not solely driven by fundamentals, but also by investor expectations, beliefs, and narratives, as emphasized in behavioral finance and narrative economics (e.g., Shiller, 2003; Shiller, 2017). In this context, sentiment analysis has emerged as a key tool to quantify the "human element", particularly through textual data (e.g. Loughran and McDonald, 2011).

Prior research has largely relied on aggregate and uniform sentiment measures, potentially obscuring important heterogeneity in how sentiment affects financial markets. REITs provide a particularly suitable setting to study those effects. They combine characteristics of real estate as an underlying asset class with stock market trading, making them sensitive to both fundamental information and the speculations and trends that stock markets experience. Their transparency, sectoral structure, and linkage to macroeconomic conditions allow for a more detailed analysis of sentiment impact. At the same time, REIT investors evaluate similar firm fundamentals but differ in their risk-return focus and their emotional link to underlying assets, making them an ideal laboratory to study heterogeneous sentiment effects across markets. It also matters whether managerial sentiment or individual sentiment on social media is looked at and if the debt or equity side of REITs is being analyzed.

This dissertation builds on the idea that economic narratives, investor emotions, and market prices are intimately linked (Maurya et al., 2026). It demonstrates that investor behavior and market outcomes cannot be understood solely through rational and quantitative determinants. By disaggregating sentiment into fundamental and non-fundamental components, the analysis reveals substantial heterogeneity across market regimes and sentiment dimensions. Paper one shows that irrational pessimistic sentiment predicts REIT returns before the COVID-19 period, while rational, fundamentals-based pessimistic sentiment becomes more relevant during the pandemic. The second paper demonstrates that ESG-related sentiment in REIT corporate disclosures is not priced uniformly. Aggregate ESG sentiment has limited explanatory power, whereas disaggregated environmental, social, and governance sentiment reveals heterogeneous investor reactions across ESG pillars and REIT sectors. Shifting the focus to debt markets, paper three shows that REIT bond investors interpret overly positive and overly negative disclosure tone as risk-relevant, while fundamentals-based and non-fundamental tone affect bond yield spreads differently.

Although the dissertation contributes to the REIT sentiment literature in several ways, it also has limitations. Since the analysis relies on specific data sources such as Twitter/X and corporate disclosures, there are limits to its representativeness across the full investor population. In addition, data availability and platform constraints, including changes in access, restrict the temporal and cross-sectional scope of the analyses. Furthermore, the use of machine learning methods involves a trade-off between flexibility and interpretability. Models such as RoBERTa and XGBoost can capture complex language patterns and non-linear relationships in data, but their results depend on training and tuning data, and sample composition.

With further developments in natural language processing, future research should evaluate generative Large Language Models (LLMs) more systematically (Chacon et al., 2025). Future studies could also broaden the range of textual data sources, including analyst reports, earnings calls, investor presentations, news articles, social media, and lender communications, to better distinguish between managerial, retail investor, analyst, institutional, and media sentiment. At the same time, the increasing use of generative AI in disclosure preparation, investor relations, and ESG communication should be accounted for (Cao et al., 2023; Kirk et al., 2025). In addition, future studies could extend the debt-market perspective beyond publicly traded REIT bonds and examine whether sentiment and disclosure tone also affect bank financing, covenants, refinancing risk, and lending relationships. Finally, REIT research should move beyond explaining market outcomes and further examine the predictive value of sentiment for REIT returns, bond yields, credit risk, and other performance measures.

From a market perspective, the findings of this dissertation carry several implications. Investors and risk managers in REIT equity and bond markets can benefit from incorporating disaggregated sentiment and ESG-related information rather than relying solely on aggregate indices or headline measures. Such granular analyses help distinguish informative signals from noise, especially during periods of heightened uncertainty. For REIT managers, the findings suggest that the tone, credibility, and consistency of corporate communication matter, particularly when overly positive or overly negative disclosure tone is interpreted as risk-relevant. It can help managers reduce information asymmetries, strengthen market confidence, and ultimately influence financing conditions and capital costs. Overall, this dissertation shows that sentiment provides valuable insights into REIT market behavior when analyzed in a disaggregated, non-linear, context- and time-dependent manner. It therefore contributes to a more granular understanding of how human perceptions, economic narratives, and financial markets interact in an era of increasing uncertainty, data availability, and methodological sophistication.

5.3 References

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