Band 115

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Real Estate Risk in Capital Markets: Evidence from REIT Debt and Equity Markets

International Real Estate Business School
Universität Regensburg

Schriften zu Immobilienökonomie und Immobilienrecht

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Die Deutsche Bibliothek – CIP Einheitsaufnahme
Jakob Kozak
Real Estate Risk in Capital Markets: Evidence from REIT Debt and Equity Markets
Regensburg: Universitätsbibliothek Regensburg 2026
(Schriften zu Immobilienökonomie und Immobilienrecht; Bd. 115)
Zugl.: Regensburg, Univ. Regensburg, Diss., 2026
ISBN 978-3-88246-546-4

ISBN 978-3-88246-546-4

Verlag: Universitätsbibliothek Regensburg, Regensburg 2026
Zugleich: Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaften, eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg
Tag der mündlichen Prüfung: 24.04.2026
Berichterstatter: Prof. Dr. Wolfgang Schäfers
Prof. Dr. Daniel Rösch

Table of Contents

List of Tables

List of Figures

1 Introduction

1.1 Motivation and Background

Real estate is an inherently heterogeneous, location-dependent, and illiquid asset class. Heterogeneity arises because different property types serve distinct user needs, generate varying cash flow patterns, and entail different cost structures, resulting in fundamentally different risk–return profiles. Location dependency implies that the location of a property cannot be altered, although it is an important determinant of a property's economic performance. Illiquidity follows from the fact that real estate is traded infrequently, in large transaction sizes, and typically with long execution periods.

Publicly listed Real Estate Investment Trusts (REITs) partially alleviate this illiquidity by transforming real estate into tradable financial assets. REITs provide investors with small-scale, high-frequency access to diversified portfolios of income-producing properties, effectively functioning as securitized real estate. Public U.S. REITs collectively hold approximately $2.5 trillion in commercial real estate assets as of 2025.[1] As listed entities, they exhibit high transparency, regularly disclosing information on the composition, location, and characteristics of their property portfolios. Moreover, regulatory payout requirements limit their capacity to retain earnings, thereby increasing their reliance on external capital.[2] Consequently, raising funds in public markets rather than private channels means that their equity and debt financing costs are determined by market pricing of risk.

The asset pricing literature on public debt markets has extensively decomposed corporate bond yield spreads into a default risk premium (Bai et al., 2020; Driessen, 2005; Huang & Huang, 2012), liquidity premium (Chen et al., 2007; Goldberg & Nozawa, 2021; Longstaff et al., 2005), tax premium (Elton et al., 2001), and equity volatility premium (Campbell & Taksler, 2003; Kim & Stock, 2014). However, despite the increasing securitization of commercial property through REITs, comparatively little is known about whether public capital markets price real estate–specific risks, in particular, those arising from property-type heterogeneity and location exposure.

Prior work, particularly Ibrahim and Falkenbach (2024), have begun to explore how geographic diversification affects REIT bond risk premia, but assume a linear relationship. Yet, modern portfolio theory (Markowitz, 1952) suggests that diversification benefits are

[1] Data on listed U.S. REITs from the National Association of Real Estate Investment Trusts (NAREIT) as of Q2 2025 (NAREIT, 2025).
[2] U.S. REITs must invest at least 75% of their assets in real estate, derive 75% of their gross income from real estate-related activities, and distribute 90% of their taxable income to investors (SEC, 2011).

inherently nonlinear, declining as portfolios become more dispersed. In addition, earlier research rarely incorporates local market volatility, even though, as implied by Merton's structural credit risk model (Merton, 1974), volatility in underlying real estate assets should directly influence default risk and therefore bond pricing.

A further location risk arises from physical climate hazards, including acute risks such as floods, hurricanes, and wildfires, as well as chronic risks such as droughts and frost periods. These risks are expected to intensify as climate change progresses, increasing both the frequency and severity of such destructive weather events (Ritchie & Roser, 2024; Shenoy et al., 2022). Existing literature has predominantly examined the impact of realized climate hazards on property valuations (see e.g., Addoum et al., 2024; Contat et al., 2024; Fisher and Rutledge, 2021; Kousky et al., 2020; Sirmans et al., 2025). Other studies have used textual measures of newspaper articles to capture physical climate risk awareness (Faccini et al., 2023). However, empirical evidence on how forward-looking expectations of physical climate risks based on climate science are priced in REIT debt and equity markets remains limited.

This dissertation addresses these gaps by examining how real estate–specific risks are transmitted into the pricing of public REIT capital markets. It aims to analyze whether and to what extent property-type characteristics, local market volatility, geographic diversification, and forward-looking physical climate risk are reflected in REIT bond risk premia and equity excess returns, thereby contributing to a more granular understanding of how real estate and capital markets are integrated. To this end, the dissertation is structured around three empirical studies. The first paper investigates whether a real estate factor is present in REIT bond risk premia and assesses the pricing implications of property-type diversification. The second paper focuses on location-based risk, examining how local market volatility and geographic diversification jointly influence REIT bond pricing. The third paper extends the analysis to forward-looking physical climate risk and evaluates how such risk is priced in both REIT bond spreads and equity excess returns.

Methodologically, the dissertation combines modern machine learning (ML) with traditional econometric approaches, leveraging the former's predictive power while retaining the interpretability of the latter. ML techniques, particularly artificial neural networks, have demonstrated strong predictive performance in asset pricing applications of stocks and government bonds due to their ability to capture complex nonlinear patterns and interactions (Bianchi et al., 2021; Gu et al., 2020; Kelly et al., 2024; Leippold et al., 2022, Leow & Lindenthal, 2025). To ensure interpretability, eXplainable Artificial

Intelligence (XAI) tools such as Accumulated Local Effects (ALE) and First-Order Feature Importance are employed alongside formal statistical inference.

Overall, this dissertation contributes to the literature on REIT risk and return, diversification strategies for real estate, and the growing application of machine learning in asset pricing. The findings have practical relevance for REIT managers, investors, and policymakers by improving the understanding of how real estate fundamentals shape the cost of capital in public markets. REIT managers benefit by being able to better time decisions about issuing and redeeming debt and equity. In addition, insights into the impact of location risk and diversification can inform longer-term portfolio strategy decisions. Investors can draw on the findings by being able to incorporate property fundamentals into their asset allocation models. Policy makers benefit from understanding the integration of real estate and capital markets, since strong integration is beneficial for efficient capital allocation and contributes to financial market stability.

1.2 Research Outline and Questions

This section describes the research outline and central research questions addressed in each of the three empirical papers. The overarching focus of the dissertation is on how location- and asset-level risks are transmitted into capital-market pricing. Each paper examines this guiding question from a distinct perspective.

Paper 1: Does Real Estate Determine REIT Bond Risk Premia?

The first research paper *Does Real Estate Determine REIT Bond Risk Premia?* lays the conceptual groundwork by examining the determinants of REIT bond risk spreads, i.e., the cost of public debt capital for REITs. Specifically, it aims to investigate whether total returns in the real estate market influence these bond spreads, and whether property type as well as property-type diversification affect REIT bond risk premia. The study adopts a dual-methodological approach: a panel regression with time and property-type fixed effects is employed to identify the statistical drivers of risk spreads, while an Artificial Neural Network (ANN) is utilized to predict REIT bond risk premia with the highest possible predictive accuracy. To enhance interpretability, Accumulated Local Effects (ALE) plots are applied to uncover the influence of individual predictors within the machine-learning framework. The following questions guide the research:

- Whether and to what extent do real estate factors, proxied by total real estate market return and REIT property type, predict REIT bond risk premia?
- Does REIT property-type diversification lead to lower risk premia?

Paper 2: Location Matters: Local Real Estate Market Risk and Geographic Diversification in REIT Public Debt

The second research paper *Location Matters: Local Real Estate Market Risk and Geographic Diversification in REIT Public Debt* aims to explore how property location affects the risk premia of REIT bonds, thereby extending the analysis of the first study. It focuses on two location-specific determinants: local real estate market volatility captured by a “local beta” and the geographic diversification of a REIT’s property portfolio, measured by the widely used Herfindahl–Hirschman Index (HHI). Methodologically, this paper first employs an ANN to achieve high predictive accuracy in modeling REIT bond risk premia, followed by ALE plots to assess nonlinear relationships, which in turn inform variable transformations used in subsequent panel regressions to test statistical significance. The research questions are as follows:

- Is there a local real estate market risk premium in REIT bonds, i.e., do investors demand higher compensation for REITs exposed to more volatile property markets?
- Does the relationship between geographic diversification and REIT bond risk premia exhibit nonlinearities?
- What is the interaction effect between local real estate market risk and geographic diversification on REIT bond risk premia?

Paper 3: Do Real Estate Capital Markets Care About Physical Climate Risk?

The objective of the third and final research paper *Do Real Estate Capital Markets Care About Physical Climate Risk?* is to assess the impact of physical climate risk expectations on REIT bond risk premia as well as REIT equity market performance. It therefore complements the first two papers and adds a perspective on the equity market as well. It uses forward-looking physical climate risk data based on climate-science for each individual REIT property. The study employs different empirical approaches to reflect the characteristics of each market. For the REIT bond market, a panel regression captures how property-level physical climate risks affect bond risk premia over time. For the REIT equity market, the Fama–MacBeth two-step regression framework identifies whether these risks are affecting equity excess returns. The research questions are the following:

- To what extent does exposure to specific property-level physical climate risks influence REIT bond risk premia, and do the effects differ across hazard types?
- To what extent does exposure to specific property-level physical climate risks influence REIT equity excess returns, and do the effects differ across hazard types?
- Does equity investor composition (institutional vs. retail) affect the extent to which physical climate risks are priced?
- Do REIT equity investors price physical climate risk projections differently depending on the assumed time horizon (current, 5, 15, or 30 years)?

1.3 Co-Authors, Submissions and Conference Presentations

The following overview provides information about co-authors, journal submissions, publication status and conference presentations.

Paper 1: **Does Real Estate Determine REIT Bond Risk Premia?**

Authors:

Jakob Kozak, Dr. Cathrine Nagl, Dr. Maximilian Nagl, Prof. Eli Beracha (Ph.D.), Prof. Dr. Wolfgang Schäfers

Submission Details:

Journal: Journal of Real Estate Finance and Economics
Current Status: Accepted (March 26, 2025) and pre-published online (June 12, 2025)

Conference Presentations:

This paper was presented at:

- the 29th Annual Conference of the European Real Estate Society (ERES) in London, UK (2023)
- the Doctoral Seminar of the Center of Finance (CoF) at the University of Regensburg in Regensburg, Germany (2024)
- the 40th Annual Conference of the American Real Estate Society (ARES) in Orlando, USA (2024)

Paper 2: Location Matters: Local Real Estate Market Risk and Geographic Diversification in REIT Public Debt

Authors:

Hendrik Jenett, Jakob Kozak, Prof. S. McKay Price (Ph.D.), Prof. Dr. Wolfgang Schäfers

Submission Details:

Journal: Journal of Property Investment & Finance
Current Status: Accepted (September 25, 2025) and pre-published online (November 10, 2025)

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: Do Real Estate Capital Markets Care About Physical Climate Risk?

Authors:

Jakob Kozak, Hannah Salzberger, Prof. Dr. Wolfgang Schäfers

Submission Details:

Journal: Real Estate Economics
Current Status: Under Review (October 30, 2025)

Conference Presentations:

This paper was presented at:

- the 31st Annual Conference of the European Real Estate Society (ERES) in Athens, Greece (2025)

This paper will be presented at:

- the 32nd Annual Conference of the Pacific Rim Real Estate Society (PRRES) in Adelaide, Australia (2026)
- the Annual Conference of the American Real Estate and Urban Economics Association (AREUEA), held jointly with the Allied Social Science Associations (ASSA) in Philadelphia, USA (2026)

1.4 References

Addoum, J. M., Eichholtz, P., Steiner, E., & Yönder, E. (2024). Climate change and commercial real estate: Evidence from Hurricane Sandy. *Real Estate Economics, 52*(3), 687–713. https://doi.org/10.1111/1540-6229.12435

Bai, J., Goldstein, R. S., & Yang, F. (2020). Is the credit spread puzzle a myth? *Journal of Financial Economics, 137*(2), 297–319. https://doi.org/10.1016/j.jfineco.2020.02.009

Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond risk premiums with machine learning. *The Review of Financial Studies, 34(2), 1046–1089 https://doi.org/10.1093/rfs/hhaa062*

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance, 58(*6), 2321–2350. https://doi.org/10.1046/j.1540-6261.2003.00607.x

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *The Journal of Finance, 62*(1), 119–149. https://doi.org/10.1111/j.1540-6261.2007.01203.x

Contat, J., Hopkins, C., Mejia, L., & Suandi, M. (2024). When climate meets real estate: A survey of the literature. *Real Estate Economics, 52*(3), 618–659. https://doi.org/10.1111/1540-6229.12489

Driessen, J. (2005). Is default event risk priced in corporate bonds? *The Review of Financial Studies, 18*(1), 165–195. https://doi.org/10.1093/rfs/hhi009

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *The Journal of Finance, 56*(1), 247–277. https://doi.org/10.1111/0022-1082.00324

Faccini, R., Matin, R., & Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance,* 155, 106948. https://doi.org/10.1016/j.jbankfin.2023.106948

Fisher, J. D., & Rutledge, S. R. (2021). The impact of Hurricanes on the value of commercial real estate. *Business Economics, 56*(3), 129–145. https://doi.org/10.1057/s11369-021-00212-9

Goldberg, J., & Nozawa, Y. (2021). Liquidity supply in the corporate bond market. *The Journal of Finance, 76*(2), 755–796. https://doi.org/10.1111/jofi.12991

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Huang, J.Z., & Huang, M. (2012). How much of the corporate-Treasury yield spread is due to credit risk? *The Review of Asset Pricing Studies, 2*(2), 153–202. https://doi.org/10.1093/rapstu/ras011

Ibrahim, I., & Falkenbach, H. (2024). Diversification and cost of public debt for REITs: Evidence from the US. *Journal of Real Estate Portfolio Management*, *30*(1), 36–53. https://doi.org/10.1080/10835547.2023.2233348

Kelly, B., Malamud, S., & Zhou, K. (2024). The Virtue of Complexity in Return Prediction. *The Journal of Finance, 79*(1), 459–503. https://doi.org/10.1111/jofi.13298

Kim, D. H., & Stock, D. (2014). The effect of interest rate volatility and equity volatility on corporate bond yield spreads: A comparison of noncallables and callables. *Journal of Corporate Finance, 26, 20–35. https://doi.org/10.1016/j.jcorpfin.2014.02.005*

Kousky, C., Palim, M., & Pan, Y. (2020). Flood damage and mortgage credit risk: A case study of Hurricane Harvey. *Journal of Housing Research, 29*(sup1), S86–S120. https://doi.org/10.1080/10527001.2020.1840131

Leippold, M., Wang, Q., & Zhou, W. (2022). Machine learning in the Chinese stock market. *Journal of Financial Economics, 145*(2), 64–82. https://doi.org/10.1016/j.jfineco.2021.08.017

Leow, K., & Lindenthal, T. (2025). Enhancing real estate investment trust return forecasts using machine learning. *Real Estate Economics*, 53, 574–606. https://doi.org/10.1111/1540-6229.12527

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance, 60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470. https://doi.org/10.2307/2978814

NAREIT (2025). *REITs by the numbers.* https://www.reit.com/data-research/data/reits-numbers

Ritchie, H., & Roser, M. (2024). *How are extreme weather events and the climate evolving in the United States?* Our World in Data. https://ourworldindata.org/us-weather-climate

SEC (2011). *Investor bulletin: Real estate investment trusts (REITs).* SEC Office of Investor Education and Advocacy. https://www.sec.gov/files/reits.pdf

Shenoy, S., Gorinevsky, D., Trenberth, K. E., & Chu, S. (2022). Trends of extreme US weather events in the changing climate. *Proceedings of the National Academy of Sciences, 119*(47). https://doi.org/10.1073/pnas.2207536119

Sirmans, C. S., Sirmans, G. S., Smersh, G. T., & Winkler, D. T. (2025). Perceptions of climate change and the pricing of disaster risk in commercial real estate. *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-025-10015-w

2 Does Real Estate Determine REIT Bond Risk Premia?

2.1 Abstract

This study is the first to examine the real estate-specific determinants of REIT bond risk premia. Using a dataset of 33,857 U.S. REIT bond yield spreads and 24 explanatory variables, we predict REIT bond yield spreads with a non-parametric artificial neural network algorithm and interpret the model's predictions using the explainable machine learning method Accumulated Local Effects Plots (ALE). We report evidence of a direct real estate factor for U.S. REIT bond yield spreads proxied by real estate market total return and REIT property type. In addition, we find a property-type diversification risk premium for REIT bonds, indicating that there is no economic benefit in the form of lower cost of bond debt for most property-type diversification at the REIT-level. We argue that this is due to higher management and valuation complexity of diversified REIT portfolios. This study's findings have relevant implications for REIT portfolio strategy and REIT capital structure decisions, as we show that specialized REITs generally have lower bond debt costs compared to diversified REITs. Moreover, a better understanding of the drivers influencing REIT bond risk premia helps investors to effectively manage bond portfolio risks.

Keywords: Yield Spread, Bond Risk Premia, REIT, Diversification Risk Premium, Machine Learning, Neural Network

2.2 Introduction

The fixed income market is a vital part of the economic system, supplying capital to businesses and governments. Therefore, it is essential for investors and policymakers to understand its risk and return characteristics. Currently, the U.S. economy experiences a significant shift, transitioning from a period of low interest rates to a rising interest rate environment. This shift, combined with increasing geopolitical tensions and a heightened sense of economic uncertainty, has created a complex market scenario. In this context, it is critical for real estate investment trusts (REITs), investors, and policymakers to understand the drivers of REIT bond risk premia in order to identify appropriate times to issue bonds, make informed investment and portfolio risk management decisions, and monitor market stability. REITs turn to bonds for financing in significant volume. In 2020, a peak year, U.S. REITs issued bonds totaling $81.55 billion. Due to rising interest rates, by 2023, this amount had decreased to $44.44 billion, still above the ten-year average before 2020 of around $40 billion.[3] Additionally, data from the National Association of Real Estate Investment Trusts (NAREIT) indicate that the share of unsecured public debt offerings by U.S. REITs, as a percentage of their total public capital offerings, increased from 26% in 1992 to 65% in the first half of 2023.[4] Despite the economic significance of REIT bonds, academic research has predominantly focused on the risk and return characteristics of REIT stocks, leaving the public debt of REITs largely unexplored.

REITs have distinctly different characteristics compared to other bond-issuing corporations. First, U.S. REITs are highly regulated entities: they must invest at least 75% of their assets in real estate, derive 75% of their gross income from real estate-related activities, and distribute 90% of their taxable income to investors (SEC, 2011). These regulatory requirements limit REITs' ability to retain earnings and reinvest internally, making them more dependent on external financing (Dogan et al., 2019). Specifically, Breuer et al. (2023) state that the average leverage ratios of U.S. REITs is twice as high as that of non-REITs (50% vs. 25%). The fact that REITs have significant amount of debt on their balance sheets is coined the REIT debt puzzle.[5] Second, REIT bonds are claims on the cash flows generated from operating commercial real estate. In contrast, corporate bonds are

[3] Source: S&P Global Market Intelligence.
[4] Based on NAREIT data: https://www.reit.com/data-research/reit-market-data/reit-capital-offerings
[5] Which of the three classical capital structure theories (trade-off theory, market timing theory and pecking-order theory) explains the debt financing decisions of REITs is disputed in the literature. The trade-off theory assumes that a company takes on debt in order to benefit from the advantages of the tax shield while accepting higher probability of bankruptcy. Since REITs are tax-exempt companies, they do not gain tax advantages through debt (Brown & Riddiough, 2003). Harrison et al. (2011) and Boudry et al. (2010) find evidence that both the trade-off and market timing theories apply to REIT debt financing. On the other hand, Morri and Beretta (2008) argue that the pecking order can explain REIT leverage decisions because debt is still less expensive than equity or other financing options.

serviced from cash flows derived from products or services. The different sources of cash flows lead to distinct risk and return profiles: real estate generates steady, often predictable rental income, while corporate earnings can be more volatile and subject to market competition and consumer preferences. Additionally, while most bond borrowing at the REIT level is unsecured, the tangible real estate assets of REITs are easier to value and monitor compared to intangible assets like intellectual property, brand, or research and development efforts that other corporations possess. Due to these fundamental structural differences, we analyze REIT bonds in isolation.

This study examines the determinants of REIT bond risk premia, i.e., the yield spread, defined as the difference between the yield to maturity of REIT bonds and government bonds of equal remaining maturity. This spread not only measures the risk perceived by the market but also signifies the firm's cost of public debt capital. The majority of work has been conducted on various parts of the corporate bond yield spread, without focusing on REIT bonds and their real estate drivers. Studies find that the corporate bond yield spread cannot be explained by default risk alone (see e.g., Bai et al., 2020; Driessen, 2005; Elton et al., 2001; Huang & Huang, 2012), but also by a tax premium (see e.g., Elton et al., 2001), liquidity risk premium (Chen et al., 2007; Goldberg & Nozawa, 2021; Longstaff et al., 2005) and equity volatility premium (see e.g., Campbell & Taksler, 2003; Kim & Stock, 2014).

From a methodological viewpoint, the literature on corporate bond yield spreads to date mostly adopts linear regression models to analyze and predict corporate bond yield spreads (see e.g., Bao et al., 2011; Campbell & Taksler, 2003; Chen et al., 2007; Collin-Dufresne et al., 2001; Elton et al., 2001; Kim & Stock, 2014; Longstaff et al., 2005). Only in the recent past have machine learning methods been used in empirical asset pricing studies to predict excess returns of stocks (Gu et al., 2020) and government bonds (Bianchi et al., 2021). Bianchi et al. (2021) state that the success of neural networks in bond price predictions is due to the model's ability to capture complex nonlinearities in the data. This is echoed by Kelly et al. (2024), who establish a theoretical underpinning to the observation that machine learning models, such as our neural network, outperform linear models. A single study to date by Kim et al. (2021) applies a battery of machine learning methods to predict corporate bond yield spreads. The authors report that a machine learning model in the form of a neural network performs best.

Hence, based on previous findings, we employ a neural network model to gain insights into the determinants of REIT bond risk premia because a high-performing model allows to make such inferences. Our aim is to predict REIT bond yield spreads and shed light on the individual importance of determinants. To achieve this, we use two model-agnostic methods for machine learning explainability: first-order feature importance and Accumulated Local Effects (ALE) plots. Our study is based on a dataset comprising 33,857 REIT bond yield spreads from 2010 to 2022, along with 24 explanatory variables. These variables encompass data from the equity market, REIT equity data, bond market, REIT bond data, REIT accounting information, as well as total returns from the direct real estate market and REIT property-type, all aiming to explain REIT bond yield spreads.

We find evidence that there is a direct real estate factor in REIT bond yield spreads by showing that real estate market total return is an important and negatively related driver of REIT bond yield spreads. This is supported by the finding that REIT property type is an important determinant as well. Surprisingly, we find indication of a property-type diversification risk premium, since property specialization is negatively related to REIT bond yield spreads compared to REITs with property-diversified portfolios for most property specializations. This means that investors generally do not reward property diversification on REIT level with a lower cost of debt. Consequently, this may suggest that investors prefer to property-diversify themselves by selecting a portfolio of specialized REITs. Additionally, the importance of the REIT's market capitalization, the bond's coupon rate, and the bond's time to maturity hints at the presence of default risk premia, tax premia and liquidity risk premia, respectively, for REIT bonds. From a methodological standpoint, we show that a deep neural network outperforms an ordinary least squares regression (OLS) in predicting REIT bond risk premia out-of-sample and attribute this not so much to nonlinearity but to interaction effects in the data as the ALE plots reveal.

This study contributes to the literature on REIT risk and return, REIT diversification and machine learning in asset pricing. First, it adds to the literature on the relationship between direct real estate and REIT return and risk characteristics. For REIT stocks, previous studies find evidence for a significant direct real estate risk premium in REIT equity returns (Clayton & MacKinnon, 2003; Kroencke et al., 2018). We find that direct real estate is also a factor in REIT bond risk premia, showing that an investor in REIT bonds is exposed to real estate market risk and property-type risk. Second, the study contributes to the REIT diversification literature by finding no advantages from property-type diversification at the REIT level in the form of lower cost of public debt. In particular, it complements Anderson et al. (2015), Capozza and Seguin (1999) and Kim et al. (2021) who study the effect of REIT-level property-type diversification on REIT performance and debt costs. Lastly, this study complements the work on machine learning in asset pricing such as Bianchi et al. (2021); Gu et al. (2020); Kim et al. (2021) by showing that a neural network outperforms an ordinary least squares (OLS) regression in predicting REIT bond yield spreads. In addition, we make the neural network interpretable by using explainable machine learning methods.

The remainder of this paper is organized as follows. The next section offers an overview of relevant related literature. Section 2.4 describes the dataset and data processing. In Section 2.5 we provide a description of the applied neural network architecture as well as explainable machine learning methods, namely first-order feature importance and Accumulated Local Effects Plots (ALE). Section 2.6 presents our findings with regard to model performance and feature importance. Section 2.7 concludes.

2.3 Literature Review

2.3.1 Corporate Bond Risk Premia Components

Studies on the real estate-specific risk premia of REIT bonds are largely missing. From a real estate standpoint, Freybote (2016) establishes a link between real estate-specific investor sentiment and REIT bond yields, regardless of the issuing REIT's credit rating. Gilstrap et al. (2022) find that REITs that are owned by institutional investors incentivized to monitor the firm have lower cost of public debt.

However, several non-real estate-specific determinants and associated risk premia for corporate bonds have been identified in the literature. Elton et al. (2001); Huang and Huang (2012) find that a portion of the corporate bond yield spread is attributed to default risk for certain bond ratings. Longstaff et al. (2005) explore this further, using credit default swap premia as a proxy for default risk. In addition, Elton et al. (2001) postulate that tax regimes in the U.S. influence yield spreads due to corporate bonds being subject to state tax, unlike government bonds. In contrast, Longstaff et al. (2005) do not find a large tax premium in corporate bond yield spreads. Also, Chen et al. (2007) find limited evidence for a significant tax effect in non-investment grade bonds. When considering bond liquidity, Longstaff et al. (2005) find a correlation between bond-specific illiquidity and yield spreads using various liquidity proxies. Bao et al. (2011) expand on this, stating that bond illiquidity is a crucial determinant in explaining corporate bond yield spreads. In addition, Chen et al. (2007) provide a comprehensive overview, taking into account a broad spectrum of illiquidity proxies, arriving at the conclusion that liquidity is a major factor in determining corporate bond yield spread variations. Also, variables from the equity market have been found to be important determinants of corporate bond yield spreads, such as the return of the S&P 500 index and CBOE volatility index as a sentiment measure (Collin-Dufresne et al., 2001). Campbell and Taksler (2003) find that company-level equity volatility has a predictive power comparable to credit ratings for corporate bond yield spreads. Chen et al. (2007) however, report limited evidence of equity volatility's significance for certain bond grades. Interest rate volatility is found to be another important determinant of corporate bond yield spread (Kim & Stock, 2014). The authors observe a relationship between interest rate volatility and yield spreads, particularly more pronounced for non-investment grade bonds.

2.3.2 Machine Learning in Risk Premia Prediction

Research using machine learning to predict bond risk premia has mainly focused on forecasting bond returns, leaving the study of yield spreads of corporate bonds, relatively unexplored. To date there is only a single study on the prediction of corporate bond yield spreads with machine learning methods from Kim et al. (2021). The authors find that a neural network with a single hidden layer, three neurons, and weight decay regularization achieves the best out-of-sample prediction as measured by the root mean square error. They find equity volatility to be the strongest predictor for yield spreads measured by its weight in the network. More studies have contributed to the research topics of predicting bond return and bond excess return predictions. Bali et al. (2020) predict corporate bond returns with 137 stock- and bond-level characteristics by using linear regression and nine machine learning methods. The results of their study show that the best performing model is a feed forward neural network with one hidden layer. Similarly, Feng et al. (2025) apply a combination of linear regressions and three different machine learning methods to predict returns of both public and private corporate bond returns, however no neural network is used for the task. Feng et al. (2025) achieve the best results with a Random Forest model. However, they note the potential for overfitting when stock characteristics are included as predictors.

Bianchi et al. (2021) are the first to use machine learning to address the issue of predictability of government bond excess returns. They follow the research design proposed by Gu et al. (2020) for predicting equity excess returns. Bianchi et al. (2021) apply different supervised machine learning models to compare their performance and a linear principal component regression to predict government bond excess returns. They conclude that neural networks deliver superior forecasts. The authors find that the inclusion of macroeconomic variables as predictors enhances model performance, boosting out-of-sample R^2 by 10 percentage points in the case of neural networks. In addition, Bianchi et al. (2021) find that bond portfolios constructed with the help of their neural network prediction model yield positive annualized certainty equivalent returns. This effect is amplified when macroeconomic data are included. Bianchi et al. (2021) and Gu et al. (2020) state the superior performance of ML-techniques in asset pricing prediction, in particular neural networks is due to their ability to model nonlinearities and nonlinear predictor interactions in the data.

2.3.3 Hypothesis Development

Our research on additional real estate drivers of REIT bond risk premia is motivated by two streams of research regarding REITs. First, there is an ongoing debate on the cointegration of the REIT stock market and the direct real estate market. Motivated by findings that REIT stock returns are largely determined by direct real estate factors (Hoesli & Oikarinen, 2021; Kroencke et al., 2018), we hypothesize that real estate variables are significant drivers of REIT bond risk premia as well. Our reasoning is that both REIT stocks and bonds constitute different claims on the same stream of cash flows generated by underlying real estate assets. Thus, if direct real estate influences REIT stock returns, it should also have an impact on REIT bond risk premia. The corresponding research question is:

1. Whether and to what extent do real estate factors, proxied by total real estate market return and REIT property type, predict REIT bond risk premia?

Second, the effects of property-type diversification at the REIT level are debated in the literature. Anderson et al. (2015) find that diversification by property-type improves REIT performance in terms of return on assets and return on equity, relative to specialized REITs. They attribute this to a larger investment opportunity set and better timing options to invest in emerging property types and to dispose of property types at their peak for diversified REITs. However, both Anderson et al. (2015) and Ro and Ziobrowski (2011) find that diversified REITs do not exhibit abnormal stock returns, aligning with the market efficiency hypothesis, which posits that their superior performance is already reflected in the market. On the other hand, Capozza and Seguin (1999) conclude that property-type diversified REITs have higher bank borrowing costs, which includes bank loans and holds true for the time period 1985 – 1992. Therefore, the effect of property-type diversification on REIT bond yield spreads (i.e. the cost of only public debt) and for REITs after 1993 is unclear ex-ante. Nevertheless, we assume that the stronger portfolio performance of diversified REITs will lead investors to price their bonds more favorably, hence leading to lower REIT bond risk premia for diversified REITs. Therefore, we formulate the following research questions:

2. Does REIT property-type diversification lead to lower risk premia?

The literature review shows that research has focused on macroeconomic, equity market, and bond market determinants of corporate bond yield spreads and their corresponding risk premia. Notably, real estate-specific determinants of REIT bond yield spreads have not been studied. Furthermore, it has been established from a methodological standpoint that machine learning methods, specifically neural networks, are highly suitable for analyzing REIT bond risk premia. Consequently, our study centers on investigating the real estate-specific factors influencing REIT bond yield spreads using neural network models.

2.4 Data

The dataset we use in this study consists of 33,857 monthly U.S. REIT bond yield spreads from 2010 to 2022. We combine different datasets, namely (1) REIT bond yield data, (2) U.S. Treasury yield data, (3) bond-specific characteristics, (4) macroeconomic data, (5) REIT-specific accounting data and equity return data, (6) bond and firm liquidity data as well as (7) data on total return of U.S. direct real estate categorized by asset type. The yield spread is the dependent variable, and it is calculated based on (1) and (2), while all other data represent the explanatory variables.

Data on REIT bond yields come from the Trade Reporting and Compliance Engine (TRACE) database provided by the Financial Industry Regulatory Authority (FINRA). Since 2002, broker-dealers have been required to self-report their over-the-counter bond transactions to the TRACE database.[6] Data on U.S. Treasury yields are from the Liu and Wu (2021) dataset, which is also used by Bianchi et al. (2021). Macroeconomic data are from the FRED-MD database as published by McCracken and Ng (2016). Equity returns data are from CRSP. REIT-specific accounting data are obtained from Compustat. Metrics on firm and bond liquidity are calculated based on TRACE data. U.S. direct real estate total return data are from the National Property Index (NPI) of the National Council of Real Estate Investment Fiduciaries (NCREIF).

The start of the observation period in 2010 is chosen for two reasons. First, only a small number of REIT bond transactions are available from the start of TRACE in 2002 through 2009, in line with observations from Freybote (2016). Second, it is well established that crisis year data from 2007 to 2009 might produce distinctly different results than the years before and after. Given the scarce data availability and related likely unreliable results, the years from 2002 to 2009 are excluded and the study focuses on the post-crisis years.

For the construction of the REIT sample no index was used to prevent survivorship bias, since only successful REITs would be included in an index. Instead, the debt offering list by the National Association of Real Estate Investment Trusts (NAREIT) forms the basis of the

[6] 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 U.S. bond transactions. However, its nature of self-reporting can lead to erroneous entries. By winsorizing our data, we try to ensure that such errors do not distort the data.

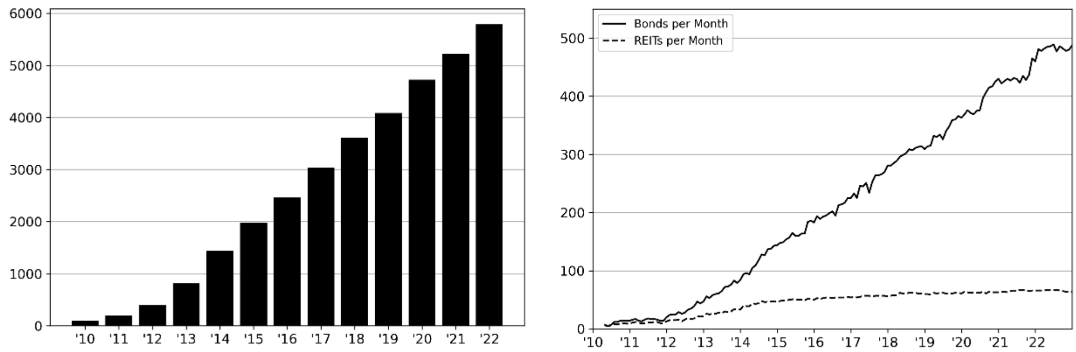
REIT sample, which includes debt offerings of all REITs, regardless of a company's success, thus providing a more accurate picture of the U.S. REIT debt market. Consequently, U.S. equity REITs that issued bonds between January 2010 to December 2022 and are listed on the NAREIT debt offering list are considered in this study.

The final dataset consists of monthly REIT bond yield spreads. The monthly yield for a REIT bond is defined as the closing yield of the last active trading day of the month. Since TRACE does not offer bond characteristics such as bond maturity date, call features, or coupon rate this data is manually collected from the FINRA website, which is based on the TRACE database. Bond transactions with missing data are excluded. Also, bonds with maturities under one month and above 30 years are excluded since no Treasury matching was feasible. Following Bessembinder et al. (2009), TRACE data entries marked as cancelled are removed from the dataset. Corrected entries are not eliminated. The bond data in TRACE includes manual reports from broker-dealers, which are prone to input errors leading to faulty data and possible outliers. Therefore, the yield spreads as well as REIT-level accounting data are winsorized monthly at the 1% and 99% percentile, respectively. Winsorizing at a monthly level prevents data leakage, i.e., no information from future observations impacts current outlier normalization. Table 2.1 offers an overview of the study's explanatory variables.

Table 2.1: Variable Descriptions

Variable		Description
Dependent Variable		
YS	Yield Spread	Difference between the yield to maturity of the REIT bond and the maturity matched Treasury yield to maturity
Real Estate Determinants		
RER	RE Total Return	National Property Index (NPI) total return by REIT property type
TYPE	Type of REIT	14 NAREIT defined REIT types based on real estate portfolio
REIT Accounting Determinants		
FFO	Funds from Operations	Funds from Operations
SIZE	Market Capitalization	Natural logarithm of market capitalization
ROA	Return on Assets	Net income divided by total assets
LEV	Leverage	Sum of long-term debt and short-term debt divided by shareholder's equity
Commercial Real Estate Sentiment		
REIS	Investor Sentiment	Real Estate Research Corporation survey-based institutional commercial real estate investors sentiment by property type
REIT Equity Determinants		
EVOL	Equity Volatility	Standard deviation of monthly excess returns over the CRSP value-weighted index over a 12-month period prior to bond transaction date
ER	Equity Return	Monthly REIT-level equity return
MB	Market-to-Book Ratio	Market value of equity divided by book value of equity
Equity Determinants		
SP500	S&P 500 Return	Return of the S&P 500 composite index
VIX	Volatility Index	CBOE volatility index
Liquidity Determinants		
BZEROT	Bond Zero Trading Days	Percentage of days in the month that the bond was not traded
FZEROT	Firm Zero Trading Days	Percentage of days in a month on which no outstanding bond of a REIT was traded
BIDASK	Bid-Ask Spread	Monthly mean of the difference in the average daily bid and ask prices of each bond
AMIHUD	Amihud Measure	Monthly mean of the daily average return divided by the traded volume in USD of that day. Introduced by Amihud (2002) and adopted for bonds by Dick-Nielsen et al. (2012)
Macroeconomic Determinants		
TS	Term Spread	10-Year Treasury rate minus 3-Month Treasury Bill
TR	Treasury Rate	10-Year Treasury rate
IVOL	Interest Rate Volatility	Standard deviation of monthly 3-month constant maturity Treasury rate over a 12-month period prior to bond transaction date
DRS	Default Risk Spread	Moody's Baa corporate bond yield minus Moody's Aaa corporate bond yield
Bond Characteristics		
TTM	Time to Maturity	Difference in months between maturity and transaction date
CR	Coupon Rate	Coupon rate on bond in percent
HY	High Yield	1 if high yield bond. 0 if investment grade bond
CALL	Callable	1 if callable. 0 if not

Figure 2.1: Yearly and Monthly Bond Transactions in Dataset



(a) Yearly Bond Transactions (b) Monthly Bond Transactions and REITs

Figure 2.1a depicts the total number of monthly bond yield spreads per year. It is evident that the number of bonds transacting on the market is relatively small in the beginning and rises sharply since 2013. Figure 2.1b shows the number of bond and REIT constituents per month. Since each bond is recorded only one time per month with its last transacted yield data, the sum of all monthly bond constituents for one year is equal to the yearly bond transactions number in Figure 2.1a. Monthly REIT constituents show the number of unique REITs that issued the bonds traded in that month. The widening spread between unique bonds per month and unique REITs per month seems to be attributable to an increase in bond issuance activity by REITs while previously issued bonds continue to trade on the market. Another more unlikely explanation is found in TRACE itself. The database was established in 2002 and introduced successively in three stages with increasing transparency specifications (Bessembinder & Maxwell, 2008). However, since the last stage was introduced in 2005, all eligible bond transactions should be reported in TRACE by 2010, when the observation period begins, so this explanation cannot account for the increase in transaction data over time. Over the entire timeline of the dataset there are 692 unique bonds transacted by 83 unique REITs. For a list of all REITs in the dataset see Appendix 2.A. The summary statistics of the winsorized dataset is depicted in Table 2.2. While uncommon, a small fraction (0.36%) of the dataset shows REIT bonds with negative yield spreads, indicating yields lower than matched government bonds. For further inspection we include a correlation matrix of the independent variables in Appendix 2.B.

Table 2.2: Summary Statistics

Variable	Unit	Mean	Median	SD	Min	Max
Yield Spread (YS)	Basis Points	149.53	129.01	102.50	-922.64	1,185.45
S&P 500 return (SP500)	Basis Points	78.35	171.81	476.81	-1,251.19	1,268.44
Volatility index (VIX)	Integer	19.51	18.35	7.32	10.08	58.08
Term spread (TS)	Basis Points	112.54	121.00	76.56	-63.00	369.00
Treasury rate (TR)	Basis Points	209.77	213.00	79.51	62.00	398.00
Interest rate volatility (IVOL)	Basis Points	2,926.03	2,185.18	3,305.88	49.30	14,676.39
Default risk spread (DRS)	Basis Points	92.30	90.00	22.46	55.00	170.00
Market-to-book ratio (MB)	Integer	3.43	2.16	3.60	0.09	24.92
Equity volatility (EVOL)	Basis Points	570.65	511.75	252.40	199.58	2,342.27
Equity return (ER)	Basis Points	66.82	76.81	796.37	-5,846.98	6,449.38
Time to maturity (TTM)	Months	94.69	80.00	74.35	1.00	360.00
Coupon rate (CR)	Basis Points	394.46	387.50	108.70	60.00	1,050.00
Leverage (LEV)	Integer	1.85	1.07	2.12	0.15	14.64
Size (SIZE)	Integer	9.38	9.38	1.08	5.67	11.80
Return on assets (ROA)	Basis Points	88.34	77.30	107.24	-456.42	1,684.29
Funds from operations (FFO)	USD MM	272.15	165.34	301.67	-241.34	1,649.00
NPI total return (RER)	Basis Points	182.77	167.70	199.39	-1,659.00	1,333.93
Investor sentiment (REIS)	Scale	4.80	4.80	0.49	3.00	6.25
Bond zero trading days (BZEROT)	Percentage	59.73	58.06	20.40	25.81	96.77
Firm zero trading days (FZEROT)	Percentage	37.69	33.33	12.88	22.58	96.77
Bid-ask spread (BIDASK)	Basis Points	96.76	59.17	117.87	0.90	3265.19
Amihud (AMIHUD)	Percentage	$2.52x10^{-6}$	$8.07x10^{-7}$	$4.85x10^{-6}$	0	$1.08x10^{-4}$
High yield (HY)	Percentage	34.85	0.00	47.65	0.00	100.00
Callable (CALL)	Percentage	70.13	100.00	45.77	0.00	100.00
Apartments	Percentage	18.50	0.00	38.83	0.00	100.00
Mixed	Percentage	2.29	0.00	14.96	0.00	100.00
Office	Percentage	10.52	0.00	30.68	0.00	100.00
Regional Malls	Percentage	6.23	0.00	24.17	0.00	100.00
Shopping Centers	Percentage	11.50	0.00	31.91	0.00	100.00
Free Standing	Percentage	10.59	0.00	30.78	0.00	100.00
Diversified	Percentage	7.24	0.00	25.92	0.00	100.00
Self-Storage	Percentage	2.82	0.00	16.56	0.00	100.00
Health Care	Percentage	11.24	0.00	31.59	0.00	100.00
Industrial	Percentage	1.99	0.00	13.96	0.00	100.00
Infrastructure REITs	Percentage	7.34	0.00	26.07	0.00	100.00
Lodging Resorts	Percentage	3.88	0.00	19.32	0.00	100.00
Specialty	Percentage	2.81	0.00	16.53	0.00	100.00
Data Centers	Percentage	3.04	0.00	17.16	0.00	100.00

Notes: Summary statistics of the dataset from 2010 to 2022 containing publicly traded U.S. REIT bonds. REIT-specific variables such as YS, ER, EVOL, MB, LEV, SIZE, ROA, FFO, REI, FZEROT, BZEROT, BIDASK, AMIHUD and RER are winsorized monthly at 1% and 99%, respectively.

2.5 Methodology

2.5.1 Artificial Neural Network

An artificial neural network (ANN) consists of an input layer, a variable number of computational layers called hidden layers, and an output layer. Additionally, a number of hyperparameters are set and tuned by a hyperparameter search procedure.[7]

In this study, we employ a randomized hyperparameter search procedure where the hyperparameter search space is not structured as a grid of individual points, as in a grid search procedure. Instead, it encompasses a distribution along which the most optimal hyperparameter combination is determined. Appendix 2.D shows the hyperparameter search spaces in detail.

To ensure that there is no overfitting of the neural network models to the training data, four regularization techniques are used in this study. First, the models use a dropout layer after every hidden layer. Srivastava et al. (2014) show that randomly dropping neurons from the neural network during training prevents overfitting. Second, all hidden layers use L2 kernel regularization. Third, an early stopping procedure prevents overfitting by stopping the training after 50 consecutive computational iterations have not improved the validation loss. Fourth, for each month to be predicted 20 instances of a model are fitted and the ten instances with the lowest validation sample loss are chosen to make out-of-sample predictions. The models' predictions are averaged and reported for this study. This equal-weighted forecast averaging procedure follows Bianchi et al. (2021).

2.5.2 Model Setups

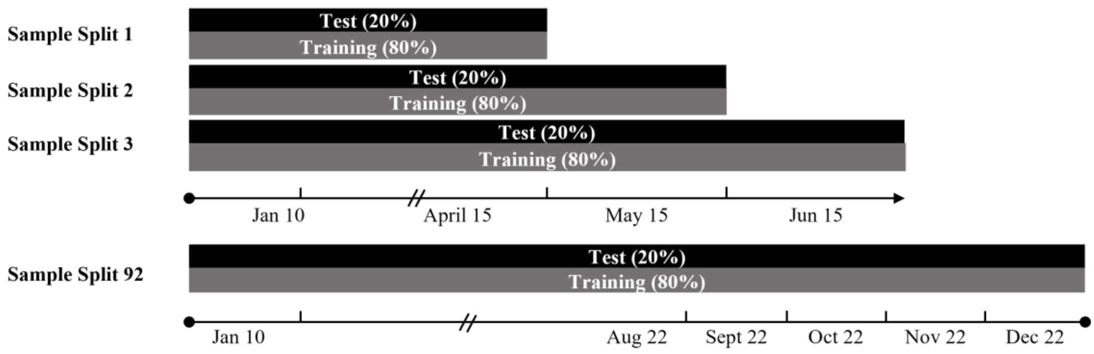
We run two different setups of both ANN and OLS with different aims. The first setup (cross-sectional splitting setup) to explain the determinants of REIT bond risk premia. Fixed time effects are included in both the ANN and the OLS to control for heterogeneity over time. In the second variant (pure prediction setup), no fixed time effects are included in the ANN and OLS models, as it only aims to predict the yield spreads of REIT bonds in the future without knowing the future time effects.

In the cross-sectional splitting setup with time fixed effects, we split our data into training (80%) of observations and testing (20% of observations). The model's hyperparameter search is done at the beginning of each year using k-fold cross-validation with k=5 folds. We expand the training and testing data by one month to account for the time variation

[7] A more detailed background description of neural networks can be found in Appendix 2.C.

of the input features. However, training and testing takes place in the cross-section. A graphical representation of the cross-sectional splitting setup is shown in Figure 2.2.

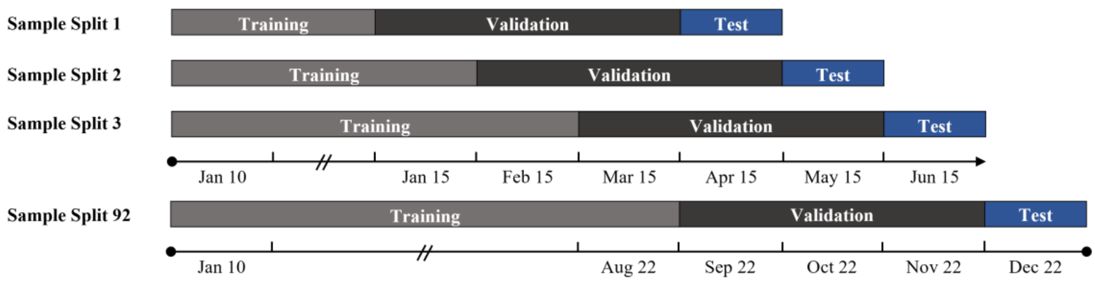
Figure 2.2: Visual Representation of Cross-Sectional Splitting Scheme



Notes: k-fold Cross Validation (k=5) and an 80% training, 20% test split.

For the pure prediction setup, we use an expanding window approach (see e.g., Bianchi et al., 2021; Gu et al., 2020). In this approach, the training and validation datasets move along the time axis as we predict different months. However, the training and validation datasets also include all past data, e.g. all past months, for training and validating the model, thus expanding the datasets. The expanding window process is depicted in Figure 2.3. The full dataset is split into three periods: (1) The test period, representing the month to be forecasted and used for evaluating model performance; (2) the validation period, which corresponds to three months preceding the test period, serving as a basis for hyperparameter optimization and (3) the training period, encompassing all months prior to the validation period, used for initial model estimation. The model's hyperparameter search is done at the beginning of each year. The sample split is moved forward each month and the model is fit again to predict one month ahead. Similar to Gu et al. (2020), no cross-validation procedure is applied to ensure that the temporal order of the data is preserved.

Figure 2.3: Visual Representation of Pure Prediction Splitting Scheme



We benchmark the neural network to a linear ordinary-least-squared (OLS) regression model. The performance metrics used to assess the performance of the neural network, and the OLS are shown in Table 2.3.

Table 2.3: Applied Performance Metrics

Error	Formula	Description
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	A higher R^2 indicates a better fit of the model.
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Sum of absolute deviations from actual to predicted values. A lower MAE indicates better model fit.
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	Sum of squared deviation from actual to predicted values. A lower MSE indicates better model fit.
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$	Sum of absolute percentage errors. A lower MAPE indicates a lower error in percent.
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Square root of sum of squared deviation from actual to predicted values. A lower RMSE indicates better model fit.

2.5.3 Feature Importance

Neural networks are often referred to as "black boxes" because it is not readily apparent how the model learns the relationships between input and output data. The branch of research that focuses on making neural networks and other machine learning methods interpretable is called eXplainable AI (XAI). To 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.

2.5.3.1 First-Order Feature Importance

We use the feature importance measure by Kellner et al. (2022) and Nagl (2023) to better understand which independent variables have the largest impact on the model's predictions. A similar method is used by Gu et al. (2020). The first order feature importance, $\theta^{\text{First}}(x_r)$, defines the overall absolute feature importance of an independent variable $r = 1, \dots, p$. It is denoted as:

$$\theta^{\text{First}}(x_r) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial f(x_i)}{\partial x_{ir}}\right)^2}, \tag{2.1}$$

where $x_i \in R^p$ is a vector of p covariates for any observation $i = 1, \dots, N$. The gradients are squared to avoid the cancellations of negative and positive values (Nagl, 2023).

Gradients naturally quantify how a change in x_r changes the prediction of $f(x_i)$ (the predicted bond risk premium), i.e., we answer the question how much our prediction changes if we change x_r by a small number. The feature importance $\theta^{\text{First}}(x_r)$ is commonly known as the (average) marginal effect of x_r in classical statistics.

2.5.3.2 Accumulated Local Effects (ALE)

The model-agnostic method of Accumulated Local Effects Plots (ALE) allows for an understanding of the effect of an independent variable on the average prediction of the dependent variable, across all values of the independent variable in the dataset. A drawback of other commonly used methods such as Shapley Additive Explanations (SHAP) by Lundberg and Lee (2017) and Partial Dependency Plots (PDP) by Friedman (2001) is that they assume that features are uncorrelated, which is rarely the case in real-world applications in finance and real estate. Accumulated Local Effects (ALE) plots introduced by Apley and Zhu (2020) solve this problem and allow features to be correlated. Therefore, ALE plots are a more robust form for understanding the effects of features on predictions. Furthermore, they find increasingly attention in the real estate literature, see, e.g., Krämer et al. (2023) or Lorenz et al. (2023).

For each feature $x_r \in R^{N\times\mathbb{1}}$, the total range of observed values is divided into K buckets. Thereby, we define $Z_{r,k}$ as the $\frac{k}{K}$ quantile of its empirical distribution. Therefore, $Z_{r,0}$ is the minimum and $Z_{r,K}$ the maximum value of Z_r. Furthermore, assume that $S_{r,k}$ defines the set of values within the left open interval from $Z_{r,k-1}$ to $Z_{r,k}$ with $n_{r,k}$ as the number of observations within the interval $S_{r,k}$. We define $k(x_r)$ as an index that returns the bucket for a value of x_r. Then, the (uncentered) accumulated local effect can be written as:

$$g_{ALE}(x_r) = \sum_{k=1}^{k(x_r)} n_{r,k}^{-1} \sum_{i \in S_{r,k}} \left[f\left(Z_{r,k}, X_{\backslash r,i}\right) - f\left(Z_{r,k-1}, X_{\backslash r,i}\right)\right]. \tag{2.2}$$

$X_{\backslash r} \in R^{N \times P - \mathbb{1}}$ denotes the set of features without the feature r of P variables and $f(.)$ describes the neural network's prediction. The minuend in the square brackets defines the prediction of $f(.)$ if the observation i is replaced with $Z_{r,k}$ and the subtrahend represents the prediction with $Z_{r,k-1}$ instead of the real value i. These differences are summed over every observation in $S_{r,k}$. This has to be done for each bucket k and, thus, $g_{ALE}(x_r)$ is the sum of the inner sums weighted by the number of observations in each bucket. Apley and Zhu (2020) define the centered accumulated local effect, with a mean effect of zero for x_r, as follows:

$$\Theta_{ALE}(x_r) = g_{ALE}(x_r) - N^{-1} \sum_{i=1}^{N} g_{ALE}\left(x_{r,i}\right). \tag{2.3}$$

Because of the centering of the ALE plot, the y-axis describes the main effect of Z_r at a certain point in comparison to the average predicted value.

2.6 Results

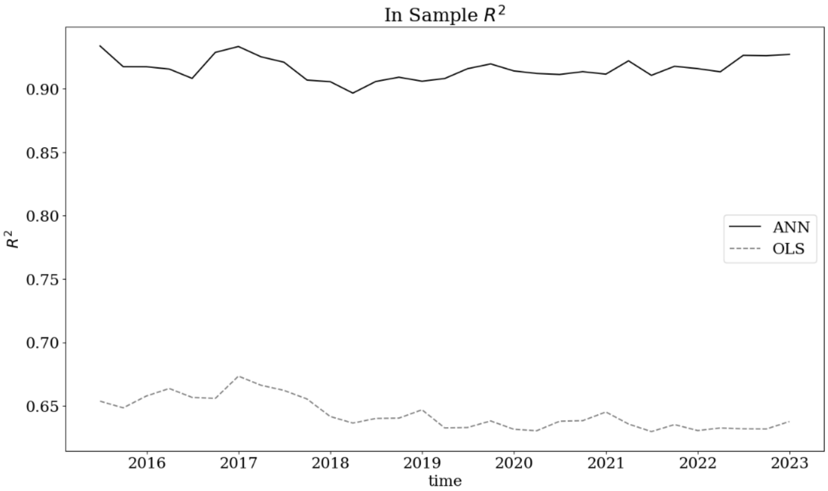
This section presents the results of the neural network and OLS model in predicting and explaining the determinants of REIT bond yield spreads for the years 2015 to 2022. Initially, the results of the cross-sectional splitting analysis of the neural network and OLS with time fixed effects are shown. Additionally, the feature importance is presented to identify the key drivers influencing REIT bond yield spreads. Further analysis is then carried out on selected features such as the property type variable, utilizing ALE plots for a more comprehensive understanding. Finally, in the out-of-sample setup (pure prediction) REIT bond risk premia are predicted with a neural network and OLS model without time fixed effects and their respective performance is presented.

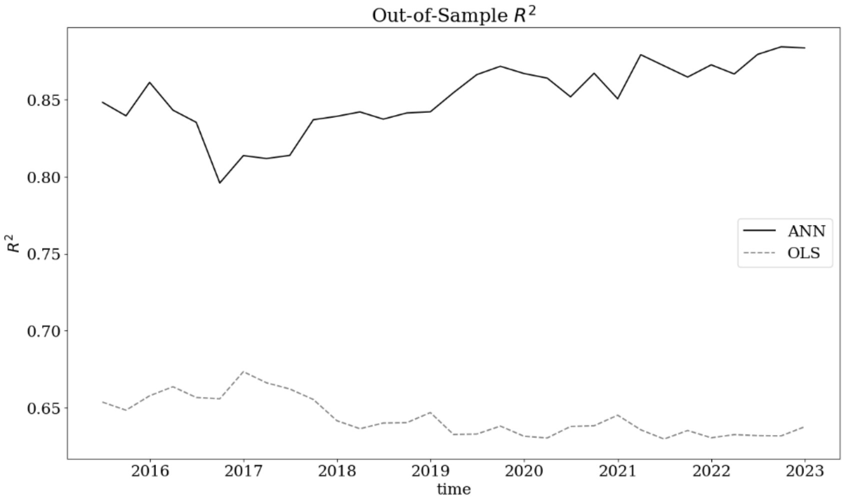
2.6.1 Explaining Determinants in the Cross-Sectional Splitting Setup

The performance of the cross-sectional splitting ANN and OLS model in form of their R^2 are depicted graphically in Figure 2.4. Table 2.4 shows an overview of all performance metrics. The ANN model outperforms the OLS during the entire sample period in-sample as well as out-of-sample. Mean R^2 of the ANN is 92% in-sample and 85% out-of-sample.

R^2 for the OLS is 64% in-sample and 62% out-of-sample. Table 2.5 reports the regression summary of the OLS with year-quarter time fixed effects and property type fixed effects. We discuss the OLS coefficients together with the significance of the first-order ANN characteristics in the next section.

Figure 2.4: Comparison of OLS and ANN Quarterly Model Performance





Notes: This panel shows the R^2 measure for the in-sample and out-of-sample portion of the data. For illustration purposes the quarterly mean is plotted. The solid black line is the performance of the neural network, and the dotted gray line shows the performance of the OLS.

Table 2.4: Comparison of OLS and ANN Model Performance

	OLS					ANN				
	MAPE	MAE	MSE	RMSE	R^2	MAPE	MAE	MSE	RMSE	R^2
In-Sample	42.17	30.14	2,294.38	47.28	0.64	16.19	14.96	533.16	22.83	0.92
Out-of-Sample	38.38	30.71	2,391.60	48.43	0.62	20.45	18.18	924.71	30.20	0.85

Table 2.5: OLS Regression Results – REIT Bond Risk Premium

Variable	Coefficient	Standard Error
RER	-35.2653***	(7.934)
SP500	3.7373*	(1.996)
VIX	32.3406***	(4.951)
TS	82.886***	(10.7)
DRS	81.5712***	(5.697)
CALL	32.1275***	(1.306)
HY	24.2966***	(1.239)
CR	75.1786***	(3.18)
TR	-38.761***	(8.164)
IVOL	50.1124***	(7.994)
TTM	31.4951***	(1.116)
ER	-47.5704***	(5.978)
EVOL	67.8039***	(3.581)
MB	-6.3251	(4.046)
LEV	24.8978***	(5.02)
SIZE	-155.7997***	(3.655)
ROA	-34.3322***	(4.179)
FFO	25.0557***	(2.941)
REIS	9.7236***	(2.5)
BZEROT	-13.7629***	(1.079)
FZEROT	-20.8136***	(1.787)
BIDASK	68.2761***	(8.256)
AMIHUD	27.8212***	(8.893)
Apartments	-11.4309***	(1.239)
Data Centers	15.6267***	(1.733)
Free Standing	-16.8721***	(1.251)
Health Care	-8.2718***	(1.286)
Industrial	1.0103	(1.872)
Infrastructure	16.2461***	(2.352)
Lodging Resorts	15.5675***	(2.025)
Mixed	-12.1009***	(1.331)
Office	-13.8011***	(1.202)
Regional Malls	-18.7952***	(2.229)
Self-Storage	-12.7815***	(1.394)
Shopping Centers	-19.0529***	(1.287)
Specialty	6.8973***	(1.892)
Year-Quarter FE	Yes	
Property Type FE	Yes	
R^2	0.64	
No. Observations	26,696	

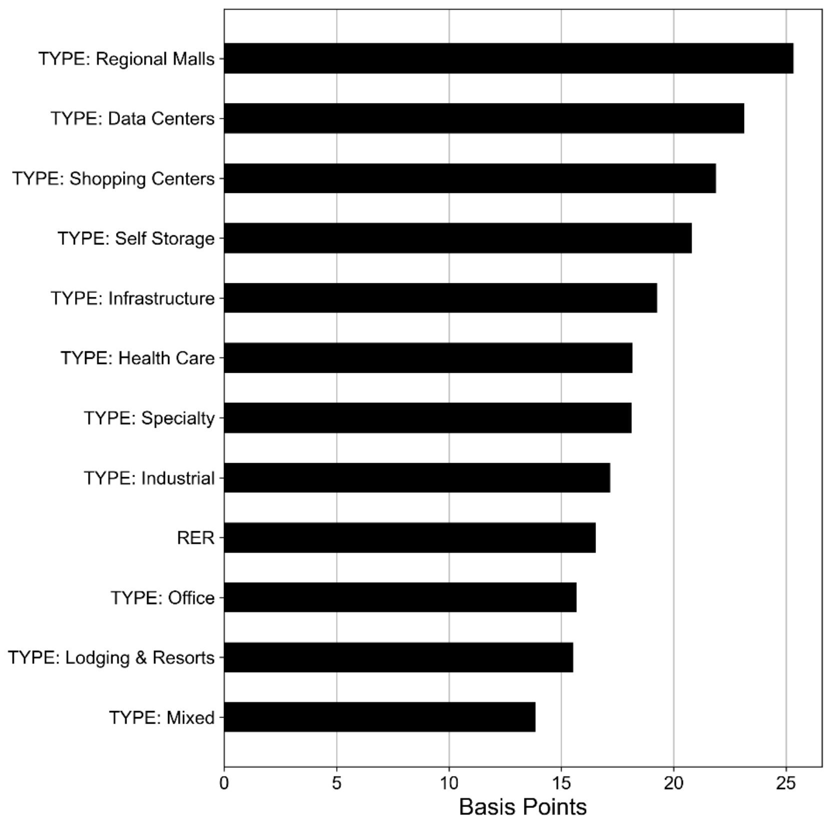
Notes: This table presents the OLS regression results regressing on REIT bond yield spread over the entire sample period from 2010 to 2022. All regressions include time and property type fixed effects. As a robustness check, a regression with firm fixed effects is also run. Results of this model specification remain robust. We report standardized regression coefficients in basis points and, in parentheses, report HAC standard errors. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively.

2.6.1.1 First-Order Feature Importance of Real Estate Variables

We first consider the first-order feature importance of the real estate-specific determinants of U.S. REIT bond yield spreads. This metric allows us to quantify the effect size of the variables for the ANN and thus draw conclusions about their economic significance. Figure 2.5 shows the mean absolute feature importance in basis points over the in-sample period from 2015 to 2022, which provides insight into the marginal effect of the variables on the prediction of U.S. REIT bond yield spreads. It is important to note that we cannot draw conclusions about the direction of the effect (i.e. positive or negative) from the absolute feature significance but rather gain an understanding of the absolute effect. In order to make statements about the direction of the effect, we refer to the sign of the OLS coefficients in the text and show the directional feature importance of the ANN as supplementary material in Appendix 2.E. The direction of the ANN feature importance as reported in the Appendix is mostly in line with the signs of the OLS coefficients.

We make a number of observations regarding the first-order feature importance. First, among the real estate-related variables, we find that the real estate market total return (RER) is an important and negatively associated variable. A higher total real estate market return in the respective REIT property sector shifts the bond risk premium in absolute numbers on average by 16.5 basis points for the ANN. This is confirmed by the OLS result, which shows a negative coefficient for the real estate return of -35.27 basis points, which is significant at the 1% level. We assume that a strong real estate market translates into less risk priced into the bonds of REITs profiting from such strong fundamentals. This contrasts Freybote (2016), who does not find a significant relationship between real estate market returns and REIT bond yields. The author argues that real estate market return does not capture forecast relevant information. However, their sample period only spans 2010 – 2013, while we analyze the years 2015 to 2022. In addition, property types are found to have a varying degree of importance for the REIT bond yield spread prediction ranging from 13.84 bps for mixed REITs to 25.33 bps for REITs holding regional malls. From the OLS results we can see that property types apartments, free standing, health care, mixed, office, regional malls, self storage and shopping centers are negatively correlated with REIT bond yield spread with significance at the 1% level compared to the reference category of the TYPE variable which is a property-type diversified portfolio. Only data centers, infrastructure, lodging/resorts and specialty property types are positively related to REIT bond yield spread with significance at the 1% level. This result is consistent with the ALE plot results on property type reported and discussed in Section 2.6.1.5.

Figure 2.5: Mean Absolute Feature Importance of Real Estate Variables



2.6.1.2 First-Order Feature Importance of Control Variables

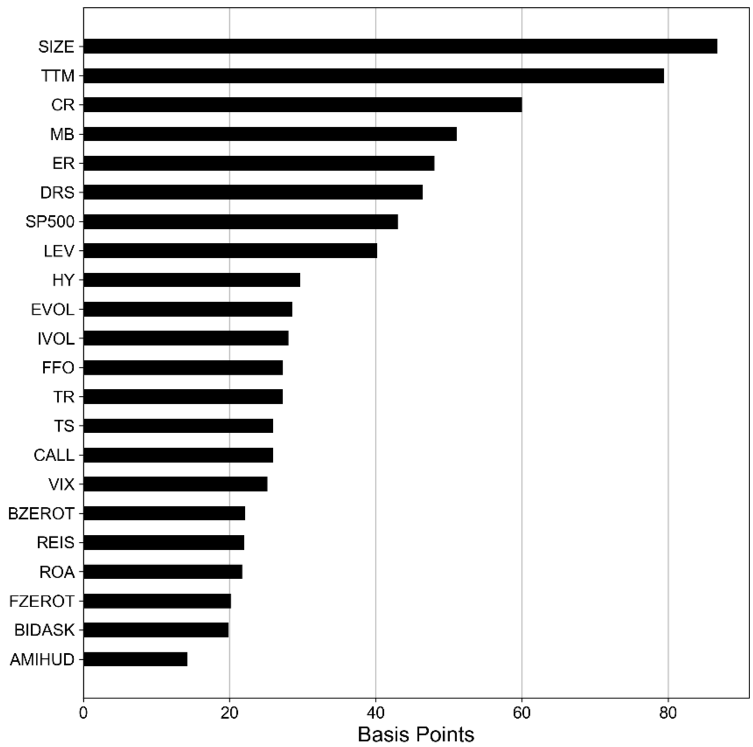
With regard to the control variables in Figure 2.6, we find that REIT size in the form of market capitalization is the most important feature for predicting U.S. REIT bond yield spreads with a mean absolute effect of 86.73 bps. It is negatively related to yield spreads, as the OLS coefficient shows, which can be explained by the fact that larger firms tend to exhibit less default risk due to revenue diversification and good access to capital markets (Lui, 2021). Therefore, investors likely expect lower risk premia for larger REITs. Also, credit rating agencies consider size to be a highly relevant determinant of default risk (Lui, 2021). This finding is in line with Kim and Stock (2014).

The second most important feature for the ANN model is the time to maturity (TTM) with a mean absolute effect of 79.44 bps. The relation of time to maturity and U.S. REIT bond yield spread is found to be positive, as shown in the OLS coefficient of 31.50 bps and, in line with Chen et al. (2007). Longstaff et al. (2005) and Nayak (2010) state that the remaining time to maturity of the bond could capture illiquidity risk.

The third most important feature is the bond's coupon rate (CR) with a mean absolute effect of 59.98 bps. There is a positive relation as shown by the OLS coefficient between the coupon rate and U.S. REIT bond yield spread, which confirms prior findings from Campbell and Taksler (2003) and Chen et al. (2007). This hints at a tax premium, since higher coupon rates lead to higher taxes. Another possibility is that the importance of the coupon rate captures an illiquidity risk premium, since higher coupon bonds tend to be less liquid than lower coupon bonds (Chen et al., 2007; Longstaff et al., 2005).

Interestingly, REIT-level equity return (ER) is the fifth most important variable (mean absolute effect 48.01 bps) with a negative relation to U.S. REIT bond yield spread according to the OLS coefficient. Notably, equity market variables like the S&P 500 return (SP500) and the CBOE volatility index (VIX) are not as important in predicting yield spreads as REIT level equity return. Also, equity return volatility (EVOL) is not among the most important variables in contrast to findings from Campbell and Taksler (2003) and Kim et al. (2021). This is an indication that REIT bond yield spreads are less driven by broad equity market variables compared to general corporate bonds but rather by REIT-specific equity returns.

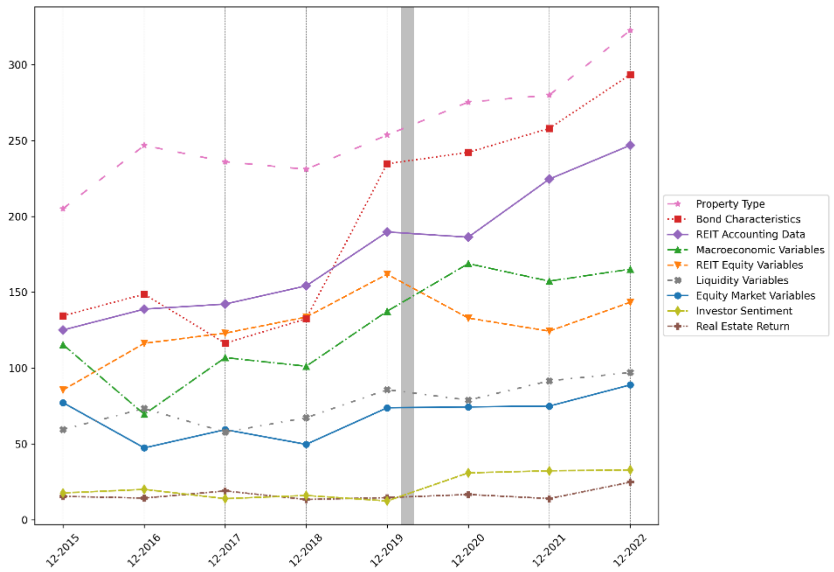
Figure 2.6: Mean Absolute Feature Importance of Control Variables



2.6.1.3 Variable Cluster Importance

For a broader overview of the determinants, Figure 2.7 clusters all variables into nine groups, namely real estate return, investor sentiment, equity market variables, REIT equity variables, macroeconomic variables, bond characteristics, REIT accounting data, liquidity variables and property type. It shows the sum of the absolute feature importance of all variables in a cluster over time.[8] Appendix 2.F gives an overview of the variables in each group. The gray shaded area marks times of U.S. economic recession according to the National Bureau of Economic Research (NBER).[9] Looking at the aggregate cluster importance of property type, it becomes evident that it is the most important variable cluster. REIT accounting data and bond characteristics are similarly important. Real estate return is not as important compared with other aggregate variable clusters. It is evident that the importance of the variable clusters stays relatively constant over time. Only the importance of property type, bond characteristics and REIT accounting data increases sharply between the beginning of 2020 and the end of 2022. The increase in the importance of REIT property type after 2020 could be due to the divergence in property fundamentals between the different property types that began with the outbreak of the coronavirus pandemic. Prior to this, most property types had robust fundamentals; however, thereafter the performance of the different property types began to diverge, increasing the overall importance of the property type invested in.

Figure 2.7: Absolute Feature Importance of Variable Groups Over Time

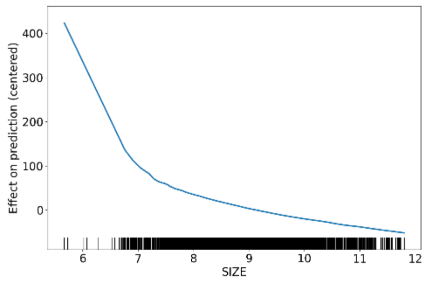


[8] Note that the graph shows the sum of the absolute feature importance of each variable in a cluster to give an insight into aggregate importance of a cluster. Unreported results of standardizing the variable clusters by dividing with the number of variables in the cluster show the average importance of a single feature in a cluster. In that analysis the importance of property type decreases.
[9] Recession indicators are accessible at https://fred.stlouisfed.org/release?rid=242

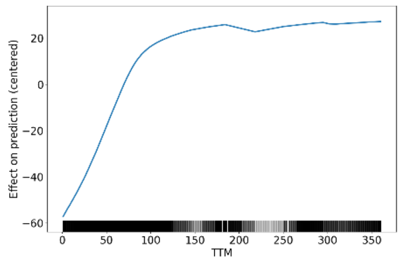
2.6.1.4 Accumulated Local Effects (ALE) of Selected Variables

Figure 2.8 shows ALE plots for the three most important variables and the total return of the real estate market. On the x-axis, the plots show the different values of the independent variables (i.e. features), while the y-axis shows the impact on the mean REIT bond yield spread prediction, measured in basis points. Put differently, the values on the y-axis indicate how much the prediction deviates from the average prediction when the features take on certain values. If the value of the y-axis is zero, it indicates the feature value that matches the average prediction of the model.

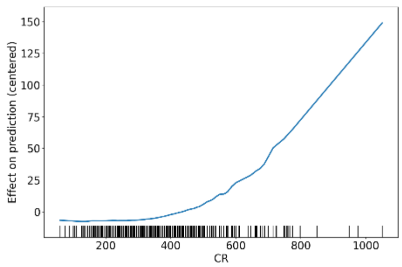
Figure 2.8: ALE Plot of Main Effects for Selected Variables



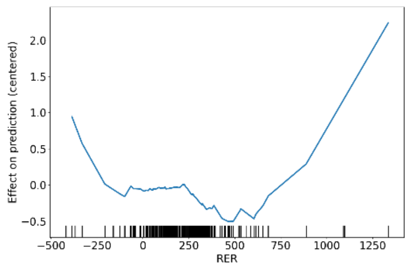
(a) Market Capitalization (log)



(b) Time to Maturity (months)



(c) Coupon Rate (bps)



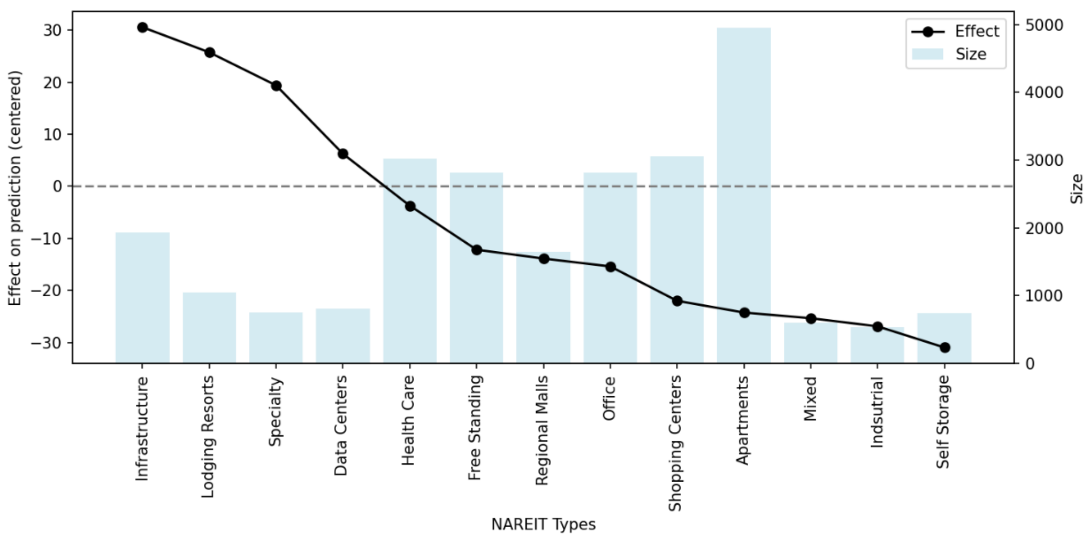
(d) Real Estate Market Total Return (bps)

The ALE plots generally validate the effects of the independent variables on the dependent variable as indicated by the first-order feature importance but offer a more detailed view. For the REIT market capitalization (SIZE), there is an evident negative relation. The mean market capitalization in the dataset, 9.38 corresponds to an average decrease of around 6 bps. The sample's smallest market capitalization corresponds to an average rise of 125 bps in the predicted REIT bond yield spread. The influence of time to maturity (TTM) is positive but approaches a maximum mean effect of around 20 basis points for a time to maturity of around 100 months and more. For a timespan below 75 months the average effect of time to maturity on REIT bond yield spreads is negative. The influence of the coupon rate is positive. The average coupon rate of around 400 bps corresponds to a mean effect on the REIT bond yield spread of -2 bps. A coupon rate of 1000 bps results in an average REIT bond yield spread increase of about 100 bps from the mean prediction. Moreover, the ALE plot for total real estate market return demonstrates that returns between 250 and 750 bps decrease the REIT bond yield spread, while lower and higher returns outside of that range increase the yield spread.[10]

2.6.1.5 Accumulated Local Effects (ALE) of Property Types

Looking at the ALE plots for the TYPE variable, which indicates the property type of a REIT, we find somewhat surprising results, as can be seen in Figure 2.9. It shows the effect on the average prediction of the model when a REIT has a portfolio specialized in a certain property type, compared to the horizontal gray dotted line representing the REIT bond yield spread of a property-type diversified REIT (reference category).[11] The bars in the background labeled as "Size" show the number of observations in the dataset for the respective property type.

Figure 2.9: ALE Plots for REIT Property Type (TYPE)



[10] Minimum-value observations with a total real estate market return of -1,659 bps (effect on mean prediction 13 bps) were truncated for the ALE plot to better graphically represent the impact for lower return values.
[11] To make a clear distinction between diversified REITs and mixed REITs we offer its official definition here: According to FTSE NAREIT's methodology, a REIT is classified as “diversified” "if it owns, manages and leases substantial assets across two or more property sectors where none meet the 75% gross invested book assets threshold for any single property sector." “Mixed” REITs, on the other hand, are essentially REITs that predominantly hold office and industrial assets. Hence the definition is: "[Mixed REITs] are not members of property sectors Industrial or Office but have a combined total of 75% or more of their gross invested book assets invested in industrial warehouses, distribution facilities and offices."

It is evident that the effect on the yield spread's predictions is only positive for four property types, namely infrastructure, lodging, specialty and data centers. All other specialized property types decrease the REIT bond yield spread compared to diversified REITs. This is in line with the statistically significant coefficients from the OLS. For example, for the ANN, the mean decrease of the REIT bond yield spread for apartment REITs is around 22 bps compared to diversified REITs. These results are surprising when thinking about yield spreads as returns, since prior studies have found property-diversification to be positively related with REIT's portfolio performance (Anderson et al., 2015; Ro & Ziobrowski, 2011). These findings are less surprising, however, when thinking about yield spreads as the cost of public debt for REITs, as Capozza and Seguin (1999) state that property-type diversification corresponds with higher bank borrowing costs for REITs. Our results therefore confirm the findings of Capozza and Seguin (1999) for public debt which has become much more relevant for REITs' capital structures over time and for a later time period. The identified diversification risk premium could be explained with investors having more difficulty in monitoring and valuing a diversified asset base (Capozza & Seguin, 1999). Also, diversified REITs could suffer from higher management complexity and costs leading to lower management efficiency (Anderson et al., 2015; Capozza & Seguin, 1999).

2.6.2 Performance in the Pure Prediction Setup

Turning to the pure prediction setup that mimics a real world use we report outperformance of the ANN compared to the OLS. Since the previously reported cross-sectional splitting approach with time fixed effects could not be properly reproduced in a real-world application in which we want to predict future time periods, we did not include temporally fixed effects in the pure prediction setup. The quarterly R^2 metric is graphically depicted in Figure 2.10. First, the ANN has a non-negative R^2 over the sample period. The ANN model performs better than the OLS during most of the out-of-sample period 2015 to 2022. This hints at nonlinearity or interaction effects in the data which the ANN can better detect and model.

All performance metrics of the ANN and OLS model are depicted in Table 2.6. The last row indicates the relative performance improvement in percentage for both models in all metrics. Interestingly, the MSE improves more than the MAE with the ANN compared to the OLS. This indicates that the ANN is better at handling large outliers compared to the OLS model. Although RMSE is derived from MSE, the lower relative improvement in RMSE compared to MSE highlights the fact that while ANN is better at reducing large errors (as shown by MSE), the overall improvement across all errors (as captured by RMSE) is somewhat less pronounced. This suggests that while ANN handles outliers better, it also improves general error reduction, albeit to a slightly lesser extent.

Figure 2.10: Quarterly Performance of OLS vs. ANN

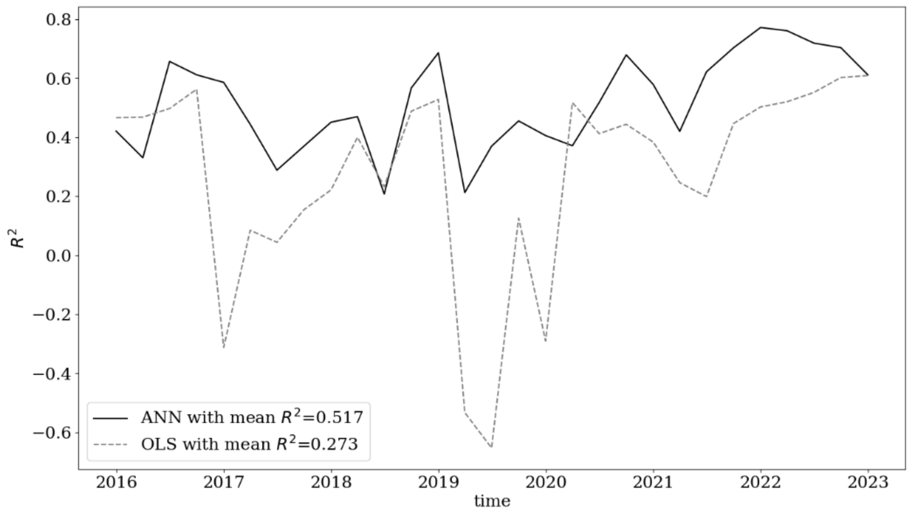


Table 2.6: Comparison of Metrics for ANN and OLS

	MAPE	MAE	MSE	RMSE	R^2
ANN	55.39	40.16	3804.71	57.70	0.52
OLS	78.20	52.24	5370.79	69.45	0.27
Δ ANN/OLS	−29.17%	−23.12%	−29.16%	−16.92%	+92.59%

2.7 Conclusion

Understanding the real estate-specific drivers that influence REIT bond risk premia is important for REITs, investors, and policymakers alike. For REITs, understanding the drivers of their yield spreads, i.e., their cost of public debt, is critical to timing new bond issues as favorably as possible and making strategic capital structure decisions. For investors, it facilitates risk management as rising yield spreads lead to a decline in bond values and vice versa. Policymakers can benefit by enacting informed regulations that promote a stable and robust market environment.

To the best of our knowledge this is the first study to predict REIT bond yield spreads and analyze its real estate drivers using a neural network model and a dataset of 33,857 REIT bond yield spreads from 2010 to 2022. We find evidence for a direct real estate factor in U.S. REIT bond yield spreads proxied by the importance of real estate market total return and REIT property type for predicting REIT bond yield spreads. Real estate market total return is negatively related to REIT bond yield spreads. We assume that REITs that benefit from strong real estate market fundamentals face lower costs of bond debt. The effect of REIT property type on bond debt costs varies by type but is generally an important determinant of REIT bond risk premia.

We also report a property-type diversification risk premium in U.S. REIT bonds, as most specialized REITs exhibit lower bond yield spreads than diversified REITs. This implies that REITs holding a property-type diversified portfolio face higher costs of public debt capital compared to REITs that specialize in a single property type. This might be explained by investors opting to create their own diversification by selecting a mix of specialized REITs. Furthermore, the asset base of a specialized REIT tends to be easier to value and monitor by investors.

In addition, in line with literature on corporate bond yield spreads in general, the feature importance of REIT market capitalization, REIT bond coupon rate and REIT bond time to maturity hints at a default risk premium, tax and liquidity risk premia for REIT bonds as well. Also, we show that a machine learning algorithm, namely a neural network outperforms an OLS regression in predicting REIT bond yield spreads in the cross-section as well as real world prediction setup. We also apply the state-of-the-art explainable machine learning methods first-order feature importance and Accumulated Local Effects (ALE) plots to explain the model's predictions.

This study adds a public debt perspective to studies from Kroencke et al. (2018) and Clayton and MacKinnon (2003) by showing that real estate is not only a factor in REIT stock returns but also in REIT bond risk premia. In addition, it complements findings on property-type diversification on REIT operational performance and borrowing costs from Anderson et al. (2015), Ro and Ziobrowski (2011) and Capozza and Seguin (1999) by showing that property-type diversification on REIT-level correlates with higher risk premia, i.e. higher cost of bond debt. It therefore has important practical implications for REIT capital structure and portfolio diversification strategies.

This research is a first stepping stone in understanding the risk premia of REIT bonds. Future research could examine the effects of REIT portfolio location on bond risk premia, in particular an analysis on geographic diversification could add valuable insights. As a neural network recognizes nonlinearity and can therefore approximate the real data generating process in REIT bond data, future research could also investigate its use in detecting bond mispricing, providing the basis for successful trading strategies.

2.8 References

Aggarwal, C. C. (2018). *Neural networks and deep learning: a textbook*. Springer.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Anderson, R. I., Benefield, J. D., & Hurst, M. E. (2015). Property-type diversification and REIT performance: an analysis of operating performance and abnormal returns. *Journal of Economics and Finance, 39*(1), 48–74. https://doi.org/10.1007/s12197-012-9232-0

Apley, D.W., & Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. *Journal of the Royal Statistical Society. Series B: Statistical Methodology, 82*(4), 1059–1086. https://doi.org/10.1111/rssb.12377

Bai, J., Goldstein, R. S., & Yang, F. (2020). Is the credit spread puzzle a myth? *Journal of Financial Economics, 137*(2), 297–319. https://doi.org/10.1016/j.jfineco.2020.02.009

Bali, T. G., Goyal, A., Huang, D., Jiang, F., & Wen, Q. (2020). Predicting corporate bond returns: Merton meets machine learning. *Georgetown McDonough School of Business Research Paper No., 3686164*. https://doi.org/10.2139/ssrn.3686164

Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. *The Journal of Finance, 66*(3), 911–946. https://doi.org/10.1111/j.1540-6261.2011.01655.x

Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2009). Measuring abnormal bond performance. *The Review of Financial Studies, 22*(10), 4219–4258. https://doi.org/10.1093/rfs/hhn105

Bessembinder, H., & Maxwell, W. (2008). Markets: Transparency and the corporate bond market. *The Journal of Economic Perspectives, 22*(2), 217–234. https://doi.org/10.1257/jep.22.2.217

Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond risk premiums with machine learning. *The Review of Financial Studies, 34*(2), 1046–1089. https://doi.org/10.1093/rfs/hhaa062

Boudry, W. I., Kallberg, J. G., & Liu, C. H. (2010). An analysis of REIT security issuance decisions. *Real Estate Economics, 38*(1), 91–120. https://doi.org/10.1111/j.1540-6229.2009.00255.x

Breuer, W., Nguyen, L. D., & Steininger, B. I. (2023). Decomposing industry leverage: The special cases of real estate investment trusts and technology & hardware companies. *Journal of Financial Research, 46*(3), 791–823. https://doi.org/10.1111/jfir.12332

Brown, D. T., & Riddiough, T. J. (2003). Financing choice and liability structure of real estate investment trusts. *Real Estate Economics, 31*(3), 313–346. https://doi.org/10.1111/1540-6229.00068

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance, 58*(6), 2321–2350. https://doi.org/10.1046/j.1540-6261.2003.00607.x

Capozza, D. R., & Seguin, P. J. (1999). Focus, transparency and value: The REIT evidence. *Real Estate Economics, 27*(4), 587–619. https://doi.org/10.1111/1540-6229.00785

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *The Journal of Finance, 62*(1), 119–149. https://doi.org/10.1111/j.1540-6261.2007.01203.x

Clayton, J., & MacKinnon, G. (2003). The relative importance of stock, bond and real estate factors in explaining REIT returns. *The Journal of Real Estate Finance and Economics, 27*(1), 39–60. https://doi.org/10.1023/A:1023607412927

Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The determinants of credit spread changes. *The Journal of Finance, 56*(6), 2177–2207. https://doi.org/10.1111/0022-1082.00402

Dick-Nielsen, J., Feldhütter, P., & Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics, 103*(3), 471–492. https://doi.org/10.1016/j.jfineco.2011.10.009

Dogan, Y. Y., Ghosh, C., & Petrova, M. (2019). On the determinants of REIT capital structure: Evidence from around the world. *The Journal of Real Estate Finance and Economics, 59*(2), 295–328. https://doi.org/10.1007/s11146-018-9687-7

Driessen, J. (2005). Is default event risk priced in corporate bonds? *The Review of Financial Studies, 18*(1), 165–195. https://doi.org/10.1093/rfs/hhi009

Elton, E. J., Gruber, M. J., Agrawal, D., & Mann, C. (2001). Explaining the rate spread on corporate bonds. *The Journal of Finance, 56*(1), 247–277. https://doi.org/10.1111/0022-1082.00324

Feng, G., He, X., Wang, Y., & Wu, C. (2025). Predicting individual corporate bond returns. *Journal of Banking & Finance,* 171, 107372. https://doi.org/10.1016/j.jbankfin.2024.107372

Freybote, J. (2016). Real estate sentiment as information for REIT bond pricing. *Journal of Property Research, 33*(1), 18–36. https://doi.org/10.1080/09599916.2016.1146791

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *The Annals of Statistics, 29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Géron, A. (2019). *Hands-on machine learning with Scikit-learn, Keras, and Tensorflow: Concepts, tools and techniques to build Intelligent systems* (2 ed.). O'Reilly.

Gilstrap, C., Petkevich, A., Sezer, O., & Teterin, P. (2022). REIT debt pricing and ownership structure. *The Journal of Real Estate Finance and Economics, 64*(4), 546–589. https://doi.org/10.1007/s11146-020-09806-0

Goldberg, J., & Nozawa, Y. (2021). Liquidity supply in the corporate bond market. *The Journal of Finance, 76*(2), 755–796. https://doi.org/10.1111/jofi.12991

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Harrison, D. M., Panasian, C. A., & Seiler, M. J. (2011). Further evidence on the capital structure of REITs. *Real Estate Economics, 39*(1), 133–166. https://doi.org/10.1111/j.1540-6229.2010.00289.x

Hoesli, M., & Oikarinen, E. (2021). Does listed real estate behave like direct real estate? Updated and broader evidence. *Applied Economics, 53*(26), 3023–3042. https://doi.org/10.1080/00036846.2020.1870921

Huang, J. Z., & Huang, M. (2012). How much of the corporate-Treasury yield spread is due to credit risk? *The Review of Asset Pricing Studies, 2*(2), 153–202. https://doi.org/10.1093/rapstu/ras011

Kellner, R., Nagl, M., & Rösch, D. (2022). Opening the black box – Quantile neural networks for loss given default prediction. *Journal of Banking & Finance, 134*, 106334. https://doi.org/10.1016/j.jbankfin.2021.106334

Kelly, B., Malamud, S., & Zhou, K. (2024). The virtue of complexity in return prediction. *The Journal of Finance, 79*(1), 459–503. https://doi.org/10.1111/jofi.13298

Kim, J. M., Kim, D. H., & Jung, H. (2021). Applications of machine learning for corporate bond yield spread forecasting. *The North American Journal of Economics and Finance, 58*, 101540. https://doi.org/10.1016/j.najef.2021.101540

Kim, D. H., & Stock, D. (2014). The effect of interest rate volatility and equity volatility on corporate bond yield spreads: A comparison of noncallables and callables. *Journal of Corporate Finance, 26*, 20–35. https://doi.org/10.1016/j.jcorpfin.2014.02.005

Krämer, B., Nagl, C., Stang, M., & Schäfers, W. (2023). Explainable AI in a real estate context – exploring the determinants of residential real estate values. *Journal of Housing Research, 32*(2), 204–245. https://doi.org/10.1080/10527001.2023.2170769

Kroencke, T. A., Schindler, F., & Steininger, B. I. (2018). The anatomy of public and private real estate return premia. *The Journal of Real Estate Finance and Economics, 56*(3), 500–523. https://doi.org/10.1007/s11146-017-9646-8

Liu, Y., & Wu, J. C. (2021). Reconstructing the yield curve. *Journal of Financial Economics, 142*(3), 1395–1425. https://doi.org/10.1016/j.jfineco.2021.05.059

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance, 60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

Lorenz, F., Willwersch, J., Cajias, M., & Fuerst, F. (2023). Interpretable machine learning for real estate market analysis. *Real Estate Economics, 51*(5), 1178–1208. https://doi.org/10.1111/1540-6229.12397

Lui, A. (2021). *Does size matter? Incorporating company size in credit risk assessment.* S&P Global Market Intelligence. https://www.spglobal.com/market-intelligence/en/news-insights/research/does-size-matter-incorporating-company-size-in-credit-risk-assessment

Lundberg, S., & Lee, S., I. (2017). A unified approach to interpreting model predictions. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*. https://dl.acm.org/doi/10.5555/3295222.3295230

McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics, 34*(4), 574–589. https://doi.org/10.1080/07350015.2015.1086655

Morri, G., & Beretta, C. (2008). The capital structure determinants of REITs. Is it a peculiar industry? *Journal of European Real Estate Research, 1*(1), 6–57. https://doi.org/10.1108/17539260810891488

Nagl, M. (2023). *Does non-linearity in risk premiums vary over time?* [Working paper]. Social Science Research Network. https://doi.org/10.2139/ssrn.4638168

Nayak, S. (2010). Investor sentiment and corporate bond yield spreads. *Review of Behavioural Finance, 2*(2), 59–80. https://doi.org/10.1108/19405979201000004

Ro, S., & Ziobrowski, A. J. (2011). Does focus really matter? Specialized vs. diversified REITs. *The Journal of Real Estate Finance and Economics, 42*(1), 68–83. https://doi.org/10.1007/s11146-009-9189-8

SEC (2011). *Investor bulletin: Real estate investment trusts (REITs).* SEC Office of Investor Education and Advocacy. https://www.sec.gov/files/reits.pdf

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research, 15*(56), 1929–1958. http://jmlr.org/papers/v15/srivastava14a.html

2.9 Appendix

Appendix 2.A – REIT List

Table 2.7: List of Aggregated REITs in Dataset

NCREIF Type - Aggregated

Index	REIT Name	Ticker	NAREIT Type
1	American Assets Trust, Inc.	AAT	Diversified
2	American Tower Corporation	AMT	Infrastructure REITs
3	Care Capital Properties, Inc.	CCP	Health Care
4	CorEnergy Infrastructure Trust, Inc.	CORR	Infrastructure REITs
5	Crown Castle International Corp. (REIT)	CCI	Infrastructure REITs
6	CubeSmart	CUBE	Self-Storage
7	CyrusOne Inc.	CONE	Self-Storage
8	Digital Realty Trust, Inc.	DLR	Data Centers
9	Diversified Healthcare Trust	DHC	Health Care
10	Duke Realty Corporation	DRE	Mixed
11	EPR Properties	EPR	Specialty
12	Equinix, Inc.	EQIX	Data Centers
13	Extra Space Storage, Inc.	EXR	Self-Storage
14	Gaming and Leisure Properties, Inc.	GLPI	Diversified
15	GEO Group, Inc.	GEO	Diversified
16	Healthcare Realty Trust Incorporated	HR	Health Care
17	Healthcare Trust of America, Inc.	HTA	Health Care
18	Healthpeak Properties, Inc.	PEAK	Health Care
19	Innovative Industrial Properties, Inc.	IIPR	Specialty
20	Iron Mountain, Inc.	IRM	Diversified
21	Lamar Advertising Company (REIT)	LAMR	Specialty
22	Lexington Realty Trust	LXP	Diversified
23	Life Storage, Inc.	LSI	Self-Storage
24	Medical Properties Trust, Inc.	MPW	Health Care
25	National Health Investors, Inc.	NHI	Health Care
26	Omega Healthcare Investors, Inc.	OHI	Health Care
27	Outfront Media, Inc.	OUT	Specialty
28	Public Storage	PSA	Self-Storage
29	Sabra Health Care REIT, Inc.	SBRA	Health Care
30	SBA Communications Corporation	SBAC	Infrastructure REITs
31	Select Income REIT	SIR	Diversified
32	Starwood Waypoint Homes	SFR	Diversified
33	Ventas, Inc.	VTR	Health Care
34	VICI Properties Inc.	VICI	Specialty
35	Vornado Realty Trust	VNO	Diversified
36	W. P. Carey Inc.	WPC	Diversified
37	Washington Real Estate Investment Trust	WRE	Diversified

Table 2.8: List of Apartment, Hotel and Industrial REITs in Dataset

NCREIF Type - Apartment

Index	REIT Name	Ticker	NAREIT Type
38	American Campus Communities, Inc.	ACC	Apartments
39	AvalonBay Communities, Inc.	AVB	Apartments
40	BRE Properties, Inc.	BRE	Apartments
41	Camden Property Trust	CPT	Apartments
42	Education Realty Trust, Inc.	EDR	Apartments
43	Equity Residential Properties Trust	EQR	Apartments
44	Essex Property Trust, Inc.	ESS	Apartments
45	Mid-America Apartment Communities, Inc.	MAA	Apartments
46	Post Properties, Inc.	PPS	Apartments
47	United Dominion Realty Trust, Inc.	UDR	Apartments

NCREIF Type - Hotel

Index	REIT Name	Ticker	NAREIT Type
48	Braemar Hotels & Resorts Inc.	BHR	Lodging/Resorts
49	FelCor Lodging Trust Incorporated	FCH	Lodging/Resorts
50	Host Hotels & Resorts, Inc.	HST	Lodging/Resorts
51	Ryman Hospitality Properties, Inc.	RHP	Lodging/Resorts
52	Service Properties Trust	SVC	Lodging/Resorts
53	Summit Hotel Properties, Inc.	INN	Lodging/Resorts

NCREIF Type - Industrial

Index	REIT Name	Ticker	NAREIT Type
54	DCT Industrial Trust Inc.	DCT	Industrial
55	First Industrial Realty Trust, Inc.	FR	Industrial
56	Prologis, Inc.	PLD	Industrial
57	Rexford Industrial Realty, Inc.	REXR	Industrial

Table 2.9: List of Office and Retail REITs in Dataset

NCREIF Type - Office

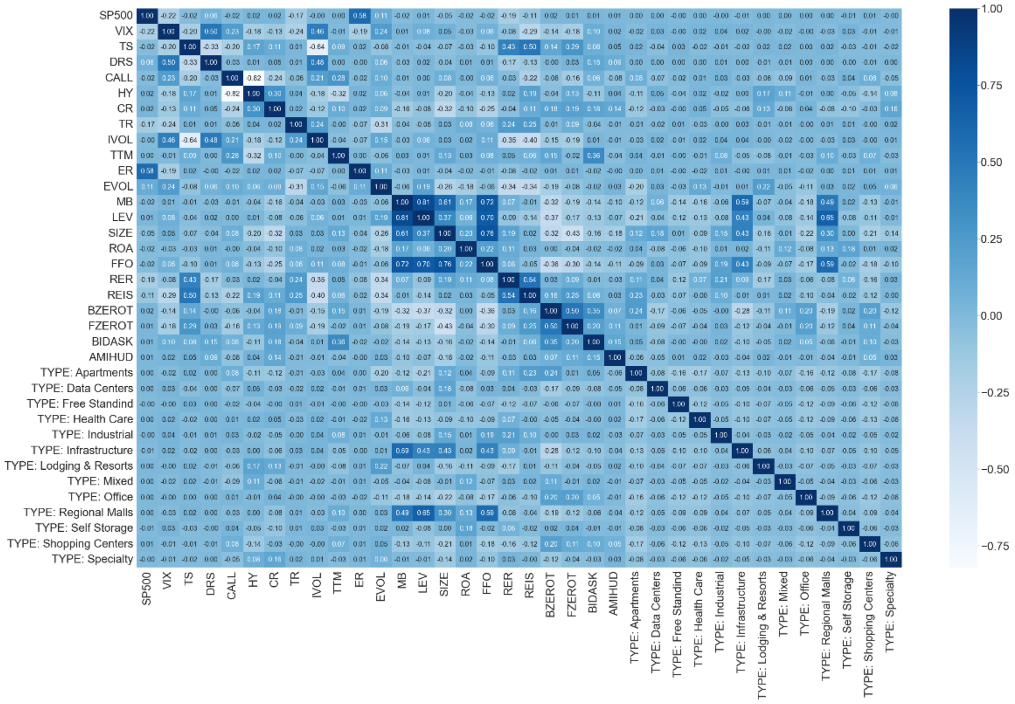
Index	REIT Name	Ticker	NAREIT Type
58	Alexandria Real Estate Equities, Inc.	ARE	Office
59	Brandywine Realty Trust	BDN	Office
60	Corporate Office Properties Trust	OFC	Office
61	Highwoods Properties, Inc.	HIW	Office
62	Hudson Pacific Properties, Inc.	HPP	Office
63	Kilroy Realty Corporation	KRC	Office
64	Office Properties Income Trust	OPI	Office
65	Piedmont Office Realty Trust, Inc.	PDM	Office
66	SL Green Realty Corp.	SLG	Office

NCREIF Type – Retail

Index	REIT Name	Ticker	NAREIT Type
67	Boston Properties LP	BXP	Free Standing
68	Brixmor Property Group Inc.	BRX	Shopping Centers
69	Equity One, Inc.	EQY	Shopping Centers
70	Excel Trust, Inc.	EXL	Shopping Centers
71	Federal Realty Investment Trust	FRT	Shopping Centers
72	Kimco Realty Corporation	KIM	Shopping Centers
73	Kite Realty Group Trust	KRG	Shopping Centers
74	National Retail Properties, Inc.	NNN	Free Standing
75	Realty Income Corporation	O	Free Standing
76	Regency Centers Corporation	REG	Shopping Centers
77	Retail Opportunity Investments Corp.	ROIC	Shopping Centers
78	Retail Properties of America, Inc.	RPAI	Shopping Centers
79	Simon Property Group, Inc.	SPG	Regional Malls
80	Spirit Realty Capital, Inc.	SRC	Free Standing
81	STORE Capital Corporation	STOR	Free Standing
82	Washington Prime Group, Inc.	WPG	Regional Malls
83	Weingarten Realty Investors	WRI	Shopping Centers

Appendix 2.B – Correlation Matrix

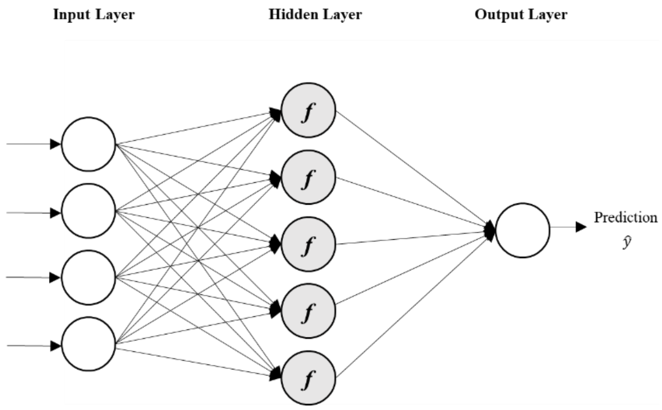
Figure 2.11: Correlation Matrix of Independent Variables



Appendix 2.C – Neural Network Background

In a neural network, data are processed from the input layer to the output layer (Goodfellow et al., 2016). A simple representation of a neural network is depicted in Figure 2.12 Each hidden layer of the neural network consists of nodes at which predictors are nonlinearly transformed. The number of nodes in the input layer depends on the number of features provided to the model, while the amount of nodes per hidden layer is chosen and optimized by the researcher.

Figure 2.12: Schematic Representation of a Neural Network



Notes: Schematic representation of a fully connected neural network with a single hidden layer. f denotes the activation functions which transform the inputs and pass them on to the next layer. It has four nodes in the input layer, five nodes in the hidden layer and one node in the output layer. Own work.

The number of nodes in the output layer depends on the desired type of output value, there is only one node in the output layer for a metric output format and there can be many nodes if the desired output format is categorical (Géron, 2019). In the case of a fully connected neural network, all nodes are connected by edges. Each connecting edge has a weight and a bias value. At each node, the weighted sum of the activations of all previous layers plus the bias of the node of the current layer is converted by an activation function and passed on to the next layer. To minimize the loss function of the network, i.e., to make more accurate predictions, the weights and biases are iteratively changed by an optimization algorithm. Crucial for network design are hyperparameters, that is, parameters that apply to the entire model and are defined ex-ante. Such hyperparameters are the activation function for each node, the number of hidden layers and nodes per layer, the loss function as well as the optimization algorithm and its learning rate (Aggarwal, 2018). The term deep learning describes the number of hidden layers implemented in the neural network. Usually, a neural network with two or more hidden layers is called a deep neural network, while less than two hidden layers represent a shallow neural network (Géron, 2019).

Appendix 2.D – Randomized Hyperparameter Search

Table 2.10: Neural Network Hyperparameter Search Spaces

Hyperparameter	**Search Space**
Learning Rate	$U^c \sim [0.0001,0.01]$
Lambda	$U^c \sim [0.000001,0.01]$
Dropout	$U^c \sim [0.1,0.4]$
Hidden Layer	$U^d \sim [1,4]$
Neuron Multiple	$U^d \sim [1,6]$

Appendix 2.E – Mean Directional Feature Importance

Figure 2.13: Mean Directional Feature Importance of Real Estate Variables

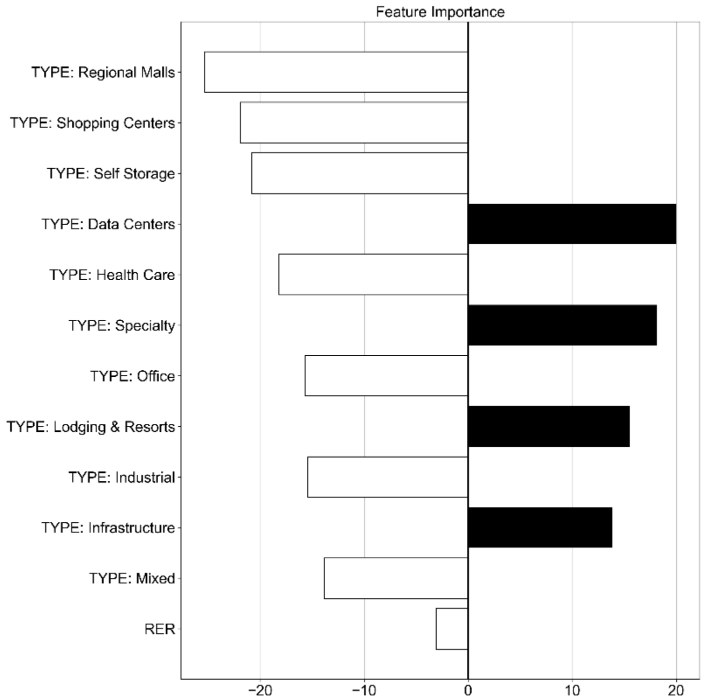
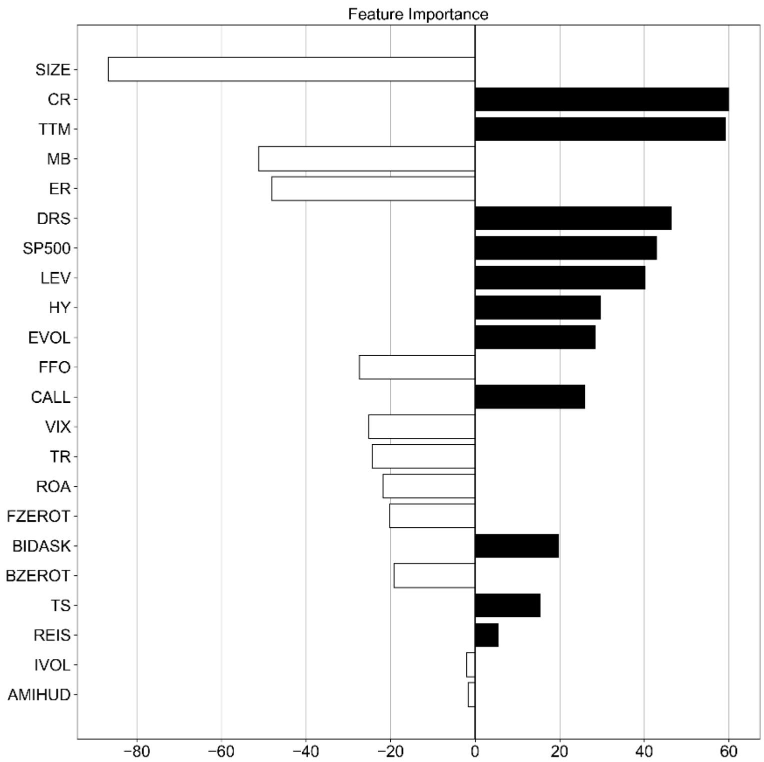


Figure 2.14: Mean Directional Feature Importance of Control Variables



Appendix 2.F – Variable Clusters

Table 2.11: Variable Clusters for Aggregate Feature Importance Analysis

Variable Cluster	Variables
Equity Market Variables	S&P 500 VIX
REIT Equity Variables	ER EVOL MB
Macroeconomic Variables	TR TS DRS IVOL
Bond Characteristics	TTM CALL HY CR
REIT Accounting Data	FFO LEV SIZE ROA
Real Estate Return	RER
Property Type	TYPE

3 Location Matters: Local Real Estate Market Risk and Geographic Diversification in REIT Public Debt

3.1 Abstract

This study examines the impact of location-based risk factors, specifically, local real estate market risk and geographic diversification, on the bond risk premia of U.S. Real Estate Investment Trusts (REITs). We quantify local real estate market risk via a REIT-specific local beta, capturing sensitivity of local real estate markets to national real estate shocks. Geographic diversification is measured using the Herfindahl-Hirschman Index (HHI). Using over 30,000 monthly REIT bond yield spreads from 2010 to 2023, we combine machine learning (ML) methods (Artificial Neural Network and Accumulated Local Effects Plots) and ordinary least squares regression with polynomial terms. We find a local real estate market risk premium for REIT bonds, indicating that investors seek compensation for the additional risk. Furthermore, we uncover a nonlinear relationship between geographic diversification and bond risk premia. While moderate diversification lowers risk premia, strong diversification increases them. The optimal point of diversification is found at an HHI of 0.25, where REITs face the lowest public debt cost. REIT managers can reduce borrowing costs by optimizing geographic diversification and avoiding overexposure to volatile markets. Bond investors can better price credit risk using REITs' local beta and diversification metrics. The study further highlights how combining ML methods with traditional regression methods can enhance model interpretability and performance.

Keywords: REIT Bond, Local Beta, Real Estate Market Risk, Geographic Diversification, Machine Learning

3.2 Introduction

Location is one of the most important value drivers for real estate. A growing body of literature examines the impact of geographic characteristics on the risk and return profiles of both private and public real estate equity investments (Fisher et al., 2022; Zhu & Lizieri, 2022). However, there is limited research on how location risks influence REIT debt. This is a notable gap, given that U.S. REITs rely heavily on bond financing to support their operations, with bond issuances remaining robust in recent years despite rising interest rates.[12] In addition, bondholders may price risk differently than equity holders because they have a higher claim priority and face primarily downside risk, as their upside potential is limited to fixed coupon payments and principal repayment.[13] Our study aims to fill this gap by investigating how location-based risk characteristics influence the pricing of REIT bonds.

Our analysis is motivated by the intuition underlying the structural credit risk model of Merton (1974), which implies that a firm's asset volatility increases its probability of default, thereby raising the required risk premium on debt. For REITs, whose assets largely consist of property holdings, local real estate market volatility affects asset value volatility, thereby raising their required risk premium on debt. On the other hand, geographic diversification may reduce asset volatility by offsetting local shocks across different real estate markets. While prior studies modeled the effect of geographic diversification linearly, we argue (drawing on modern portfolio theory) that the benefits of diversification diminish as exposure becomes more widespread. Accordingly, we assume a nonlinear relationship between geographic diversification and debt risk premia.

Building on this theoretical premise, we examine the relationship between these two location-based characteristics (local real estate market risk and geographic diversification) with REIT bond risk premia. Based on Zhu & Lizieri (2022), we construct a local beta factor to measure an individual REIT's sensitivity to local real estate market risk. This beta reflects the sensitivity of each local real estate market's total return in which a REIT holds assets to shocks in the aggregated national real estate market total return, thereby capturing the REIT's exposure to higher-risk markets. Our local beta is calculated at the granular level of U.S. Core-Based Statistical Areas (CBSA) to account for the heterogeneity of real estate markets. Additionally, to capture geographic diversification of a REIT's property portfolio, we calculate the Herfindahl-Hirschman Index (HHI).

[12] In 2020, a record-setting year with historically low interest rates, REITs issued \$81.55 billion in bonds. However, with the rise in interest rates, this figure stabilized to \$48.1 billion by 2024, slightly above the ten-year average of approximately \$40 billion prior to 2020.

[13] Indeed, recent studies on empirical asset pricing (i.e., Gospodinov & Robotti, 2021) suggest that robust evidence for common factors in pricing across equities and bonds remains elusive.

We employ a dataset of 30,186 monthly bond yield spreads from 2010 to 2023, along with 27 explanatory variables. The data include REIT bond information, property location data, REIT-specific accounting measures, equity market data and macroeconomic indicators. In our empirical analysis, we combine machine learning (ML) and traditional econometric methods, leveraging the former's ability to capture complex, nonlinear patterns while retaining the interpretability offered by the latter, as demonstrated in prior studies (see e.g., Krämer et al., 2023a, 2023b; Lorenz et al., 2023). Specifically, we employ an artificial neural network (ANN) model to predict REIT bond yield spreads. The data patterns are then visualized using the eXplainable Artificial Intelligence (XAI) method, Accumulated Local Effects (ALE) plots. These visualizations guide the selection of model specifications for the final step, where we apply a traditional ordinary least squares (OLS) regression with polynomial transformations based on the inflections identified in the ALE plots, to provide clear measures of statistical significance.

The results show a local real estate market risk premium for REIT bonds. Investors demand higher compensation for holding bonds from REITs with property portfolios in locations that are more sensitive to real estate market shocks. This effect is consistently observed across all REITs, regardless of whether they operate in more volatile or more stable markets. Consistent with our hypothesis, the effect is less pronounced than the findings for REIT equities by Zhu and Lizieri (2022), likely due to the differing priority of claims, as bondholders have higher priority than equity holders and are therefore less sensitive to geographic risks.

Additionally, the results reveal a more nuanced, nonlinear relationship between geographic diversification and REIT bond risk premia than previously reported in the literature. For REITs with more concentrated portfolios, increasing geographic diversification leads to a decrease in bond risk premia, reflecting that the benefits of diversification, such as reduced cash flow volatility and lower exposure to local economic shocks, outweigh the potential increased costs associated with managing a dispersed property portfolio. However, for REITs that are already well-diversified, further diversification results in higher bond risk premia, suggesting that the costs of additional diversification exceed its benefits. This pattern aligns with modern portfolio theory, which posits that diversification initially reduces risk, but its marginal benefits diminish as portfolio diversification increases (Markowitz, 1952). The turning point occurs at an HHI value of 0.25, where we identify a structural break in the data that marks a shift in how investors price the risks of further diversification. This point can be seen as the optimal portfolio diversification for minimizing the cost of public debt from a REIT perspective. When interacting local beta with HHI, we find that for REITs operating in more volatile markets, the effect of geographic concentration on bond risk premia is amplified, resulting in a disproportionately larger increase in risk premia as concentration rises.

This study makes several contributions to the literature on REIT bond pricing and geographic diversification. First, we add to Zhu & Lizieri (2022) as well as Fisher et al. (2022) by showing that local real estate market risk affects REIT public debt, which constitutes a major funding source for REITs. Second, we refine the notion of the previously documented geographic diversification discount, contrasting with prior work that specifies geographic diversification effects in a linear form (e.g., Feng et al., 2021; Hartzell et al., 2014; Ibrahim & Falkenbach, 2024; Ro & Ziobrowski, 2011). Third, we show that the cost of concentration rises nonlinearly in high-risk markets, amplifying bond risk premia beyond what either factor would suggest in isolation. Taken together, our findings enhance the understanding of how REIT bondholders price risk and underscore the importance of considering both real estate market conditions and portfolio structure when evaluating debt costs. Lastly, we demonstrate that combining ML and traditional methods can enhance model interpretability and accuracy.

Overall, this study offers practical insights for REIT managers, investors, and bond portfolio managers. REIT managers can use these findings to optimize their real estate market allocations and reduce their cost of public debt. For bond portfolio managers and investors, our analysis of local beta provides a valuable tool for assessing REITs' sensitivity to local market shocks when making investment and hedging decisions.

The remainder of this paper is organized as follows. Section 3.3 provides an overview of the related literature and derives the research questions. Section 3.4 outlines the dataset, data processing steps and the construction of the key variables. Section 3.5 details the applied methods, followed by the empirical findings presented in Section 3.6. Finally, in Section 3.7, the paper concludes with a summary of insights and implications.

3.3 Literature Review

This study touches on two strands of literature: (1) the impact of location-specific risks on firm performance and asset pricing and (2) the role of diversification, particularly geographic diversification, in shaping REIT value, performance, and debt costs.

3.3.1 Location and Firm Risk

A growing body of finance literature emphasizes the role of firm location in determining risk exposure and financial outcomes. Several studies develop local beta factors to capture sensitivity to geographically specific shocks. Tuzel and Zhang (2017), for example, measure the sensitivity of local industrial production to national GDP shocks, showing that high-beta metropolitan areas experience greater cyclicality in both wages and real estate prices. Fisher et al. (2022) apply a similar approach in the REIT context, linking location density and systematic stock risk exposure to rental growth and cap rates.

Zhu and Lizieri (2022) introduce a real estate-specific local beta, measuring the sensitivity of local property market returns to national real estate market returns. Their findings indicate that REITs with high local beta, particularly those with geographically concentrated portfolios, exhibit higher equity returns, reflecting compensation for greater location-based risk.

3.3.2 Diversification and REIT Performance, Valuations and Debt Costs

A second body of literature analyzes the effect of property-type and geographic diversification on REIT equity performance, valuations and debt costs. While Ro and Ziobrowski (2011) find no significant difference between specialized and diversified REITs in terms of equity excess returns, Benefield et al. (2009) document outperformance for diversified REITs during favorable market conditions. In contrast, European real estate companies (Haran et al., 2020) show that property-type diversification is associated with lower equity returns, underscoring regional differences in outcomes. Taken together, the mixed findings highlight the challenges of isolating diversification effects and their influence on equity performance.

In terms of valuation, several U.S.-focused studies report a “diversification discount” for geographically diversified REITs (Feng et al., 2021; Hartzell et al., 2014; Huerta & Mothorpe, 2024). However, this effect is moderated by institutional ownership and transparency. Huerta and Mothorpe (2024) further argue that moderate geographic clustering can enhance operational efficiency.

Evidence on debt costs is more limited but similarly nuanced. Capozza and Seguin (1999) find that REITs with diversified property types face higher bank borrowing costs, potentially due to increased information asymmetries. This is echoed by Cheok et al. (2011) for the Asian property markets, by showing that regionally diversified REITs face higher interest expenses. Demirci et al. (2020) refine this notion by showing that property-type diversification is associated with higher spreads on bank loans and mortgages, whereas geographic diversification leads to lower spreads. Their findings suggest that, overall, diversification can reduce the cost of debt by enhancing creditworthiness through risk dispersion. On the public debt side, Ibrahim and Falkenbach (2024) provide evidence that geographic diversification is associated with higher REIT bond spreads, though they do not consider nonlinearities or interactions with location-specific risk. However, from a modern portfolio theory perspective, the relationship between diversification and risk is inherently nonlinear (Markowitz, 1952). Early diversification reduces idiosyncratic risk, while the benefits taper off at higher levels due to increasing correlations among assets. In the context of our study, higher correlations among regions and rising operational complexity may induce the diminishing effect of geographic diversification.

Taken together, these strands reveal that diversification effects differ depending on type (property vs. geography), outcome (equity returns, firm valuations or private vs. public debt costs) and geography (USA, Europe and Asia). Yet, the role of geographic diversification in REIT bond pricing, particularly its potential nonlinearities and interaction with local market risk, remains underexplored. Our study addresses this gap by adopting a granular, asset-level approach and a machine learning framework to detect nonlinear patterns.

3.3.3 Hypothesis Development

Our research is conceptually grounded in the structural credit risk model of Merton (1974), which posits that a firm defaults when the value of its assets falls below the face value of its liabilities at maturity. A key implication of the model is that asset volatility increases default probability, as it raises the likelihood that asset values will breach the default threshold. In the case of REITs, whose asset base largely consists of commercial real estate, this volatility is closely tied to fluctuations in the value of their property portfolios. We capture this through a local beta factor, which measures a REIT's exposure to volatility in local real estate markets and thus serves as a proxy for location-based asset risk. A higher local beta implies greater exposure to volatile markets, increasing asset value uncertainty and, by extension, the likelihood of default. Accordingly, bondholders should demand a higher risk premium to compensate for this increased credit risk. At the same time, such volatility may offer upside potential for equity holders through higher returns, highlighting the asymmetry between debt and equity financing. This reasoning supports our hypothesis that REITs with greater exposure to local real estate market risk will face higher bond yield spreads. Therefore, we formulate the following research question:

1. Is there a local real estate market risk premium in REIT bonds, i.e. do investors demand higher compensation for REITs exposed to more volatile property markets?

In addition, we argue that geographic diversification of a REIT’s property portfolio may lower asset volatility and default risk by mitigating location-specific exposures. However, in line with modern portfolio theory, we expect this effect to be nonlinear, with diminishing or even adverse impacts at higher diversification levels. Based on this, we state the second research question:

2. Does the relationship between geographic diversification and REIT bond risk premia exhibit nonlinearities?

Finally, if both local market risk and portfolio concentration affect bond risk premia, their interaction could be particularly relevant. For example, REITs operating in volatile markets may benefit more from diversification, while concentration in such markets could amplify default risk. This motivates our third research question:

3. What is the interaction effect between local real estate market risk and geographic diversification on REIT bond risk premia?

3.4 Data and Variable Construction

The sample used in this study consists of 30,186 monthly bond yield spreads of 60 U.S. equity REITs that are constituents of the FTSE NAREIT Index from January 2010 to December 2023.[14] The observation period starts in 2010 due to very limited REIT bond transaction data prior to this year, as noted by Freybote (2016). Therefore, the study excludes 2002 – 2009 and focuses on the post-crisis years. The dataset is based on different data types, namely (1) REIT bond data, (2) REIT property data, (3) REIT-specific accounting/market data and (4) macroeconomic data.

3.4.1 REIT Bond Risk Premium

Data on REIT bond yields come 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.[15] We calculate monthly yield spreads by averaging the volume-weighted yields of all transactions in a month of a REIT bond and then subtracting the yield on U.S. Treasuries with corresponding maturities. U.S. Treasury data come from the Liu and Wu (2021) dataset. Since TRACE does not offer bond characteristics such as the bond maturity date, call features or coupon rate, these data were manually collected from the FINRA website, which is based on the TRACE database. Bond transactions with missing data are excluded. Also, bonds with maturities under one month and above 360

[14] 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.

[15] As bonds are trades 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 U.S. However, its nature of self-reporting can lead to erroneous entries. By winsorizing our data, we try to ensure that such errors do not distort the data.

months are excluded since no Treasury matching was feasible. Following Bessembinder et al. (2009), TRACE data entries marked as cancelled are removed from the dataset, while corrected entries are kept. Furthermore, bond and firm liquidity metrics are included in the sample, as detailed in Table 3.2.

3.4.2 Local Real Estate Market Beta

Our primary research objective is to document the relationship between the systematic risk of local property markets and the risk premium of REIT bonds. Therefore, we construct our local market risk factor, referred to as local beta, using total returns from 136 CBSA divisions in the NCREIF Property Index (NPI) and REIT property portfolio data from S&P Capital IQ. First, we calculate β_c, which denotes the sensitivity of local commercial real estate prices in each CBSA to systematic real estate shocks and is calculated as follows:

$$r_{c,t}^{NPI} - r_{f,t} = \alpha_c + \beta_c\left(MKT_t^{NPI} - r_{f,t}\right) + \varepsilon_{c,t}, \tag{3.1}$$

where $r_{c,t}^{NPI}$ is the NCREIF real estate total return in CBSA c in month t and $r_{f,t}$ the risk-free rate, measured by the yield on the 1-month Treasury bill. MKT_t^{NPI} is the mean NPI across all CBSAs in month t and represents the national real estate market total return. We compute the monthly total return of each CBSA and across all CBSAs, in excess of the risk-free rate.[16] We then regress the CBSA-specific excess return on the overall market excess return to estimate β_c, which captures the sensitivity of the monthly excess return on a given CBSA portfolio to fluctuations in the overall market's excess return. Even though the NCREIF return data is available for different property types, we opt to use the aggregate total return to circumvent issues with sparse data, which could potentially lead to unreliable results.

Next, we calculate local beta for REIT i at time t – representing the mean systematic risk across all CBSAs where the REITs' properties are located – as follows:

$$\beta_{i,t}^{REIT} = \sum_{c=1}^{C} w_{i,c,t} \times \beta_c, \tag{3.2}$$

where β_c is the CBSA beta, and $w_{i,c,t}$ is the weight assigned to each CBSA, measured as the exposure of REIT i in CBSA c in month t. We calculate this exposure as the number of properties held by REIT i in CBSA c in month t divided by the number of total properties held by REIT i at time t across all C CBSAs.

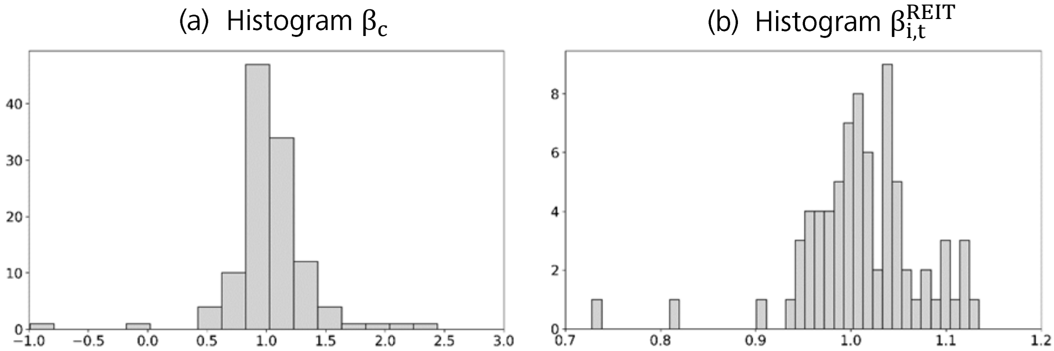
[16] While the NCREIF total return index is only published on a quarterly basis, the risk-free rate is at monthly frequency and hence we can derive a varying monthly difference between these two.

Although β_c is constant over time, $\beta_{i,t}^{REIT}$ adjusts whenever there are changes in a REIT's property portfolio. The variable $\beta_{i,t}^{REIT}$ represents a REIT's exposure to the cyclical behavior of the local real estate markets across the various CBSAs where it holds commercial property investments. For robustness reasons, we additionally calculate a rolling β_c based on a 12-month window. The construction and OLS results can be found in Appendix 3.A. Zhu and Lizieri (2022) prove that the local real estate market risk, as defined in this study, is non-diversifiable. Hence, it should be priced in the bond yield spread even for investors with diversified REIT bond portfolios.

The distributions of β_c and $\beta_{i,t}^{REIT}$ are displayed in Figure 3.1. Table 3.1 reports the five highest and lowest β_c's as well as the five highest and lowest $\beta_{i,t}^{REIT}$'s. Looking at the histograms, we can observe that most β_c's lie between 0.5 and 1.5, with only a few observations on the outer bounds. On the contrary, the relatively narrow range of REIT-specific betas, $\beta_{i,t}^{REIT}$, suggests that REITs typically maintain geographically diversified portfolios, which helps smooth out exposure to high- or low-beta CBSAs and manage overall risk more effectively. Peoria, IL and Albany-Schenectady-Troy, NY are the only CBSAs with a negative beta, indicating that the commercial property markets in these areas move inversely to the national market. As a result, they can provide a hedge against national market trends. On the other side of the spectrum, California-Lexington Park, MD; Wilmington, NC; and Cleveland-Elyria-Mentor, OH, have betas exceeding two. This suggests that these areas are highly sensitive to aggregate real estate shocks. For example, the β_c of Wilmington can be interpreted as follows: if the overall market total return increases by 1 percentage point, the return in the specific CBSA increases by 2.362 percentage points. Hence, the real estate market in Wilmington is overly reactive to changes in the aggregate real estate market.

On the $\beta_{i,t}^{REIT}$ side, the three REITs with the lowest beta are Diversified REITs. For example, the $\beta_{i,t}^{REIT}$ of Alexander & Baldwin, Inc. can be interpreted as follows: if the overall market total return increases by 1 percentage point, the property-weighted total return of all CBSAs where this REIT holds assets increases by 0.728 percentage points. Therefore, this REIT is less sensitive to aggregate real estate market shocks.

Figure 3.1: Distribution of Local Betas



Notes: The figure plots the distribution of the CBSA beta β_c and the average REIT-specific local beta $\beta_{i,t}^{REIT}$, which is based on the REITs property portfolio. The mean CBSA beta is 1.045 and the mean REIT-specific local beta is 1.012. The number of observations for β_c corresponds to the total number of CBSAs and the number of observations for $\beta_{i,t}^{REIT}$ corresponds to the total number of REITs in the study.

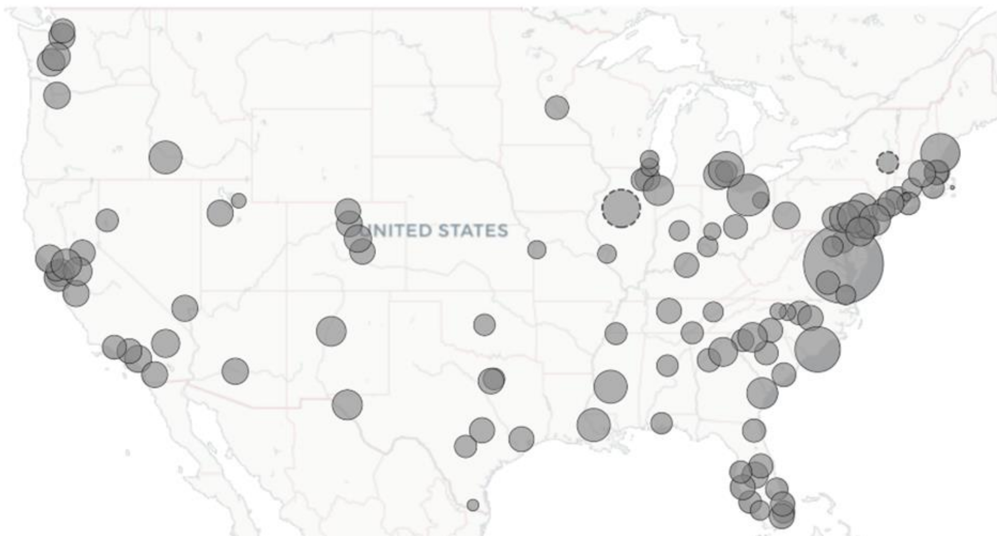
Table 3.1: Highest and Lowest Beta CBSAs and REITs

CBSA Name	$\boldsymbol{\beta_c}$
Lowest $\boldsymbol{\beta_c}$ CBSAs	
Peoria, IL	-1.796
Albany-Schenectady-Troy, NY	-0.899
Palm Bay-Melbourne-Titusville, FL	0.015
Barnstable Town, MA	0.490
New Haven-Milford, CT	0.539
Highest $\boldsymbol{\beta_c}$ CBSAs	
California-Lexington Park, MD	6.276
Wilmington, NC	2.362
Cleveland-Elyria-Mentor, OH	2.077
Rockingham County-Strafford County, NH	1.873
Warren-Troy-Farmington Hills, MI	1.641
REIT Name	$\boldsymbol{\beta_{i,t}^{REIT}}$
Lowest $\boldsymbol{\beta_{i,t}^{REIT}}$ REITs	
Alexander & Baldwin, Inc.	0.728
Essential Properties Realty Trust, Inc.	0.811
Broadstone Net Lease, Inc.	0.910
Innovative Industrial Properties, Inc.	0.936
Office Properties Income Trust	0.944
Highest $\boldsymbol{\beta_{i,t}^{REIT}}$ REITs	
Sun Communities, Inc.	1.135

Sotherly Hotels Inc.	1.121
Kimco Realty Corporation	1.121
Retail Opportunity Investments Corp.	1.116
Rayonier Inc.	1.110

Figure 3.2 illustrates the β_c distribution across the U.S., with each circle denoting one CBSA. The size of each circle is proportional to the absolute value of the respective β_c (i.e. the higher β_c, the larger the circle on the map), while the two negative values have dashed frames. Coastal CBSAs, especially those on the East Coast, are more sensitive to aggregate real estate shocks than inland CBSAs. The average beta of all coastal CBSAs is 1.12, while the average beta for all inland CBSAs is 0.97 (coastal is defined as <100 km from the coast). Zhu and Lizieri (2022) show that there is a significant positive relationship between local beta and measures of land regulatory strictness, while the most restricted markets are located along the northeast coast (from Boston through Washington D.C.) and the west coast (Seattle, San Francisco and Los Angeles).

Figure 3.2: Geographic Distribution of CBSA Betas



Notes: The figure plots the geographic distribution of CBSA betas. The size of the circles proportionally coincides with the absolute value of the betas. Negative betas have a dashed frame. Obviously, the circles only cover a small area of the U.S. However, these are the most populated areas and, therefore, contain a large share of the commercial real estate. Only those CBSAs for which a NCREIF NPI total return value exists for at least two years are included in the analysis.

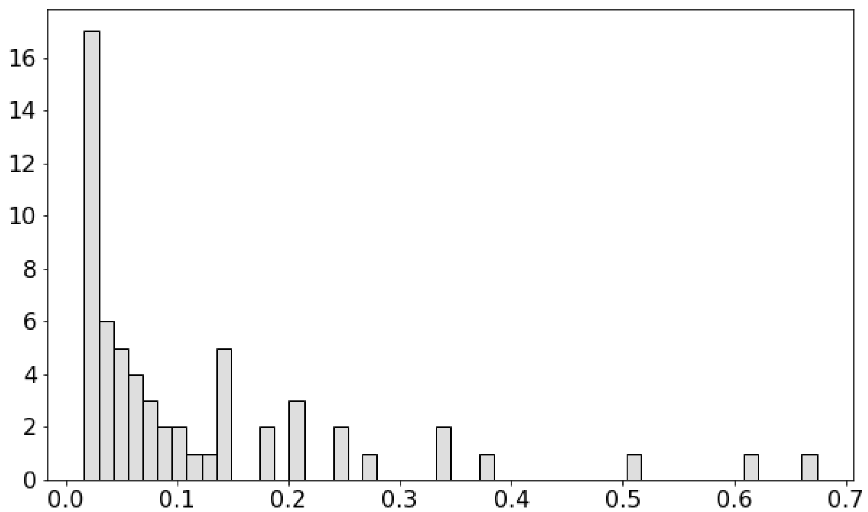
3.4.3 Geographic Diversification

In addition, following Ibrahim and Falkenbach (2024), who established a negative, linear relationship between regional concentration and REIT bond risk premia, we also account for market concentration using the HHI. It measures the geographic concentration of a REITs' property portfolio at month t and is calculated as:

$$HHI_{i,t} = \sum_{c=1}^{C} \left(\frac{P_{i,c,t}}{N_{i,t}} \right)^2 , \tag{3.3}$$

where $P_{i,c,t}$ is the number of properties of REIT i in CBSA c at time t, and $N_{i,t}$ is the total number of properties of REIT i at time t. HHI values can range from zero to one, with higher values indicating greater portfolio concentration. A value of one signifies that all properties are situated within a single CBSA. Figure 3.3 shows the histogram for the HHI. Generally, the REIT portfolios tend to be very diversified across the U.S., with a mean value of 0.0822 and most observations below 0.2. The correlation coefficient between HHI and $\beta_{i,t}^{REIT}$ is 0.038, indicating a slightly positive relationship, suggesting that REITs with more concentrated portfolios may be more exposed to market risks due to missing diversification.

Figure 3.3: Distribution of HHI



Notes: The figure plots the distribution of the independent variable HHI. For each REIT, the mean HHI value is reported. Therefore, the total number of observations corresponds to the total number of REIT in this study. The histogram reveals a right-skewed distribution, as most values are close to zero, indicating property diversification.

3.4.4 REIT-Specific and Macroeconomic Control Variables

Monthly REIT market and quarterly REIT accounting data come from Refinitiv Eikon and comprise various relevant firm characteristics. Since not all REITs in the NAREIT index have debt offerings, we only draw REIT-specific data for those REITs that have been issuing bonds over the sample period, i.e., matching the bond data. Moreover, a REIT property sector dummy is also included, with "Diversified" as the reference category. Of the 174 REITs that were NAREIT constituents at any time between 2010 and 2023, 89 REITS have been issuing bonds. Due to missing property data reports of some REITs, we end up with a sample of 60 REITs.

Macroeconomic data are from the Federal Reserve Economic (FRED) monthly database, as presented by McCracken and Ng (2016). These measures include overall economic indicators such as GDP and unemployment rate, as well as equity and debt market metrics. Debt market metrics include the term spread and default risk spread, which serve as bond market risk exposure indicators. On the equity side, the S&P 500 index and CBOE volatility index are utilized. A comprehensive overview of all variables used in this study can be found in Table 3.2.

Various steps are undertaken to preprocess the combined dataset. The $\beta_{i,t}^{REIT}$ and HHI are lagged as we want to use the current information to predict the following month. To address potential reverse causality, we perform Granger-causality tests, which show that local beta and HHI affect bond risk premia (at lags 3–5 and 4–5, respectively), while bond risk premia have no significant impact on them. We handle missing values by imputing data for up to one year, meaning that an existent value is being perpetuated until a new value occurs or 52 weeks have passed. The bond data in TRACE include manually reported information from broker-dealers, which can be prone to input errors, potentially leading to inaccurate data and outliers. Therefore, the yield spreads and REIT-level accounting data are winsorized at the 5% and 95% percentile to prevent outliers from distorting the results. This process is conducted monthly to ensure that future data points or REITs not included in the sample at a specific time are not incorporated. Finally, we standardize the features on a scale from -1 to 1 before feeding them into the model for training and testing. This is to ensure that importance weights are not biased by variable magnitudes. An overview of the summary statistics of the utilized variables is provided in Table 3.3.

Table 3.2: Variable Descriptions

Variable	Description
Dependent Variable	
Bond Risk Premium	Difference between the volume-weighted yield to maturity of the REIT bond and the maturity-matched Treasury yield to maturity
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
Bond Yield	Effective rate of return to maturity weighted by volume
Time to Maturity	Difference in month 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	
Local Beta	Local real estate market risk of a REIT based on its property portfolio
HHI	Geographic concentration of REIT properties across the CBSAs
Market Capitalization	Measure of company size, expressed as total dollar market value of a REIT's outstanding shares of stock (in million USD)
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
Return on Asset	Net Income divided by total assets
Funds From Operations	Cash flow from operations
Leverage	Total debt outstanding divided by total assets
Dividends	Distribution of a REIT's earnings to its shareholders
Market-to-Book	Market capitalization divided by total assets minus total outstanding debt
Property Type Dummy	8 REIT sectors based on property portfolio, defined by NAREIT, reference category is Diversified
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)

Table 3.3: Summary Statistics

Variable	Unit	Mean	SD	Min	Max
Dependent Variable					
Bond Risk Premium	Decimal	0.0149	0.0092	-0.143	0.0637
Bond Variables					
Coupon Rate	Decimal	0.039	0.0114	0.0075	0.0975
Bond Price	U.S.-Dollar	100.21	10.8518	10.1375	176.504
Transaction volume	U.S.-Dollar	477,288	523,365	1,000	5,000,000
Bond Yield	Decimal	0.038	0.0271	-1.8324	0.8897
Time to Maturity	Months	98	81	2	359
Credit Rating Dummy	Percentage	0.6077	0.4883	0	1
Call Status Dummy	Percentage	0.9608	0.194	0	1
Liquidity Variables					
Bond Zero Trading Days	Decimal	0.5952	0.2013	0.2581	0.9677
Firm Zero Trading Days	Decimal	0.3531	0.0902	0.2258	0.9000
Bid-Ask Spread	Decimal	0.0091	0.0092	0.0006	0.1305
REIT-Specific Variables					
Local Beta	Integer	1.0172	0.0422	0.7357	1.296
HHI	Integer	0.0822	0.0887	0.0155	0.7921
Market Capitalization	Mil. $ (log)	23.2652	0.9565	20.2933	25.53
Return	Decimal	0.003	0.0768	-0.6003	0.4559
Return on Asset	Decimal	0.0081	0.0073	-0.0163	0.1681
Funds From Operations	Integer	5.1158	3.601	0.436	16.542
Leverage	Decimal	0.4843	0.1164	0.2716	0.8075
Dividends	U.S.-D	3.263	2.2666	0.04	11
Market-to-Book	Integer	2.232	1.3562	0.3581	8.2112
Health Care REIT	Decimal	0.1169	0.1169	0	1
Hotel REIT	Decimal	0.0253	0.1571	0	1
Industrial REIT	Decimal	0.0385	0.0385	0	1
Office REIT	Decimal	0.1612	0.3677	0	1
Residential REIT	Decimal	0.2288	0.4201	0	1
Retail REIT	Decimal	0.2792	0.4486	0	1
Specialized REIT	Decimal	0.131	0.3374	0	1
Diversified REIT	Decimal	0.019	0.0467	0	1
Equity Market Variables					
S&P 500	Integer	3,295.39	925.593	1,079.8	4,685.05
VIX	Integer	19.1419	6.8775	10.0785	58.0813
Macroeconomic Variables					
Term Spread	Decimal	-0.0082	0.0275	-0.0662	0.0356
Default Risk Spread	Decimal	0.0094	0.0021	0.0055	0.017
Interest Rate Volatility	Decimal	0.0041	0.0043	0.0001	0.0157
Unemployment Rate	Decimal	0.0485	0.0196	0.034	0.148
GDP	Integer	20,661.5	1,342.44	16,582.7	22,679.3

3.5 Methodology

The methodological approach of this study is based on a combination of ML methods and traditional econometric models, motivated by the need to uncover complex, nonlinear relationships in the data while retaining interpretability and statistical rigor. Prior studies (e.g., Krämer et al., 2023b; Lorenz et al., 2023) have shown that such hybrid approaches, particularly when combined with XAI methods like ALE plots, can enhance both predictive accuracy and theoretical insight by linking flexible model structures with transparent, hypothesis-driven inference.

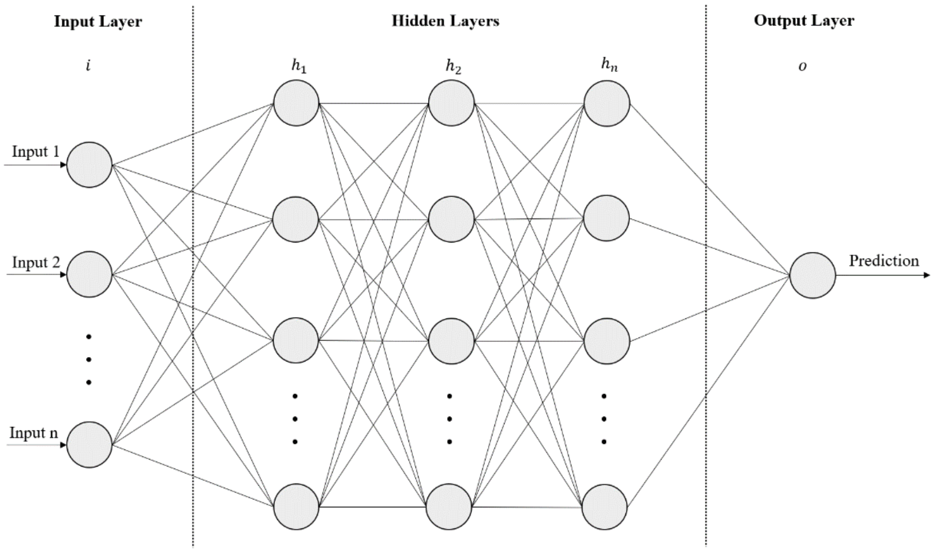
Therefore, we first employ an ANN with an expanding window scheme to derive predictions based on the preprocessed data. Subsequently, we make use of ALE plots to allow for an interpretation of the potential nonlinear impacts of the variables on the average REIT bond risk premium prediction. We then specify an OLS regression with polynomial transformations based on the insights of the ALE plots.

3.5.1 Artificial Neural Network

Prior studies on REITs have shown the superior performance of ANNs over traditional regression methods due to their ability to address the nonlinearity and non-stationary data properties (see e.g., Loo, 2020; Serrano & Hoesli, 2007). We chose an ANN over simpler nonlinear models, such as Generalized Additive Models, because its structure is even more flexible and allows us to capture complex interactions and inflection points without imposing restrictive functional assumptions. Prior studies suggest that such machine learning approaches yield more meaningful and accurate predictions compared with both linear and semi-parametric alternatives (Krämer et al., 2023b; Lorenz et al., 2023).

The structure of an ANN consists of three types of layers: an input layer, a variable number of computational layers called hidden layers and an output layer. In the input layer, each node represents one independent variable. In the hidden layers, the variables are transformed nonlinearly and passed onto the next layer. Eventually, the output layer contains the predicted bond risk premium. Figure 3.4 illustrates a simplified ANN used in the study.

Figure 3.4: Exemplary ANN Architecture



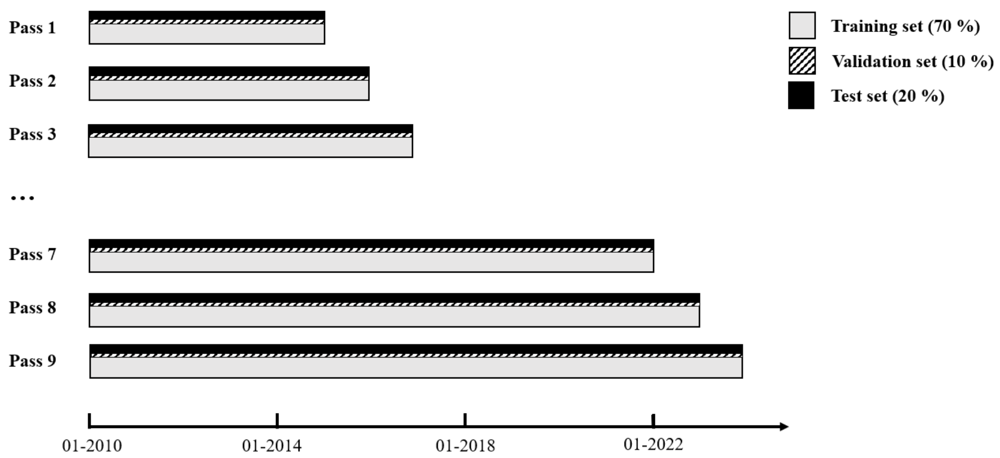
Additionally, a number of hyperparameters are defined and tuned by a hyperparameter search procedure. In this study, we use a randomized hyperparameter search method where the search space spans a distribution, allowing us to identify the most optimal hyperparameter combination. Appendix 3.B shows the hyperparameter search spaces in detail.

To prevent overfitting of the ANN models to the training data, this study employs four regularization techniques. First, a dropout layer is added after every hidden layer. Srivastava et al. (2014) prove that randomly dropping neurons along with their connections during training significantly reduces the overfitting of ANNs. Second, an L2 kernel regularization is used in the hidden layers, allowing weight penalties during the optimization process. Third, an early stopping parameter is added to the training process, terminating the optimization when the validation loss fails to show improvement over 50 consecutive iterations. Fourth, for each month in the prediction process, 20 ANNs are fitted and the 10 instances exhibiting the lowest validation loss are chosen for the out-of-sample predictions. The models' predictions are averaged and reported for this study. Using the mentioned regularization tools simultaneously can improve model performance, as shown by Gu et al. (2020).

3.5.2 Model Setup

An expanding window approach based on Gu et al. (2020) is used to deal with the time-series nature of the data. The expanding window process is illustrated in Figure 3.5. During the first iteration, 70% of the data from the first five years is utilized for training, 10% for validation and the remaining 20% is reserved for testing. The model's hyperparameter search is done at the beginning of each year using the training and validation data. With every iteration, the dataset expands by one year to account for the time variation of the input features. Fixed time effects are included to control for heterogeneity over time. The main advantage of this approach is that the algorithm tests on unseen data and can provide unbiased, robust results.

Figure 3.5: Cross-Sectional Expanding Window Approach



3.5.3 Accumulated Local Effects (ALE)

ANNs are often referred to as "black boxes" because it is not readily apparent how the model learns the relationships between input and output data. The branch of research that focuses on making ANNs and other ML methods interpretable is called XAI. 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 Shapley Additive Explanations (SHAP) by Lundberg and Lee (2017) 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 (2020), 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. (2023a, 2023b) or Lorenz et al. (2023).

The total range of observed values for each independent variable $x_r \in R^{Nx\mathbb{1}}$ is split into K bins. We define $Z_{r,}$ as the $\frac{k}{K}$ quantile of its empirical distribution with $Z_{r,0}$ being the minimum and $Z_{r,K}$ the maximum value of Z_r. Moreover, assume that $S_{r,k}$ defines the set of values within the left open interval from $Z_{r,k-1}$ to $Z_{r,k}$ with $n_{r,k}$ being the number of observations within the interval $S_{r,k}$. We define $k(x_r)$ as an index that returns the bin for a value of x_r. Consequently, the (uncentered) accumulated local effect is given by:

$$g_{ALE}(x_r) = \sum_{k=1}^{k(x_r)} n_{r,k}^{-1} \sum_{i \in S_{r,k}} \left[f\left(Z_{r,k}, X_{\setminus r,i}\right) - f\left(Z_{r,k-1}, X_{\setminus r,i}\right) \right], \tag{3.4}$$

where $x_{\setminus r} \in R^{NxP-\mathbb{1}}$ denotes the set of features without the feature r of P variables and $f(.)$ the network's prediction. The quantity in the squared brackets delineates the prediction of f(.) if the 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 summed over every observation in $S_{r,k}$. Since this has to be done for each bin k, $g_{ALE}(x_r)$ denotes the sum of the inner sums weighted by the number of observations in each bin (Apley & 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:

$$\Theta_{ALE}(x_r) = g_{ALE}(x_r) - N^{-1} \sum_{i=1}^{N} g_{ALE}\left(x_{r,i}\right). \tag{3.5}$$

Centering the individual ALEs ensures that the final ALE plot remains interpretable. In this context, the plot consistently illustrates the impact of a feature as a function of the average prediction of the ANN across the entire feature space. The visual analysis of ALE plots allows us to detect any nonlinear relationships between the independent variables and the predicted bond risk premium.

3.5.4 Ordinary Least Squares Regression

A crucial limitation of ML methods such as ANNs is their lack of interpretability regarding statistical significance, which motivates the complementary use of an OLS regression. In this regression, all variables for which nonlinear relationships were found in the ALE plots are modeled as the nth degree polynomial based on the inflection points observed in the data. The OLS is set up on a cross-sectional basis with an expanding window and time-fixed and property-fixed effects. We estimate the following linear regression model using monthly REIT bond yield spreads:

$$r_{i,t}^{REIT} - r_{i,t}^{Treasury} = c_0 + \beta_1 \beta_{i,t}^{REIT} + \beta_2 HHI_{i,t} + X_{i,t}'\theta + \gamma_t + \gamma_p + \varepsilon_{i,t}, \quad (3.6)$$

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 matched maturity i at time t. $\beta_{i,t}^{REIT}$ is the local real estate market beta and $HHI_{i,t}$ is the geographic diversification of REIT i at time t. $X_{i,t}$ denotes a vector of control variables, including bond characteristics, liquidity controls, REIT-specific variables, equity-market controls, and macroeconomic factors. γ_t are year-fixed effects, γ_p are property-type fixed effects, and $\epsilon_{i,t}$ is the error term. Table 3.4 shows the different performance metrics used to evaluate the ANN and OLS.

Table 3.4: Applied Performance Metrics

Error Metric	**Formula**
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\bar{y})^2}$
Mean Squared Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i \rvert$

3.6 Results

The following section provides the results of our empirical analysis. First, we analyze the ALE plots (specifically for local beta and HHI) to assess nonlinear relationships between these variables and the REIT bond risk premium. Second, we specify an optimized OLS based on the uncovered nonlinear data patterns in the ALE plots including all control variables. We then assess the drivers of REIT bond risk premia, focusing on local real estate market risk, geographic concentration and their interplay.

3.6.1 Results Accumulated Local Effects (ALE) Plots

To better understand the influence of a single feature on the ANN model's predictions, we turn to the ALE plots, visualizing the data patterns uncovered by the ANN. The ALE plots show how a feature interacts with the target variable REIT bond risk premia. The values on the y-axis show how much the risk premia prediction deviates from the average prediction when the variable takes on certain values indicated on the x-axis. The results of the ALE plots can be used to improve the performance of other parametric or semi-parametric models by specifying the functional form for each feature. To assess the presence of nonlinearities in the data, we display a univariate OLS fitted line in red alongside the effect direction of the ANN as shown in the ALE plot. We can then conclude whether the OLS can capture the functional form of the variables well or whether it should be specified manually based on the uncovered patterns of the ALE plots.

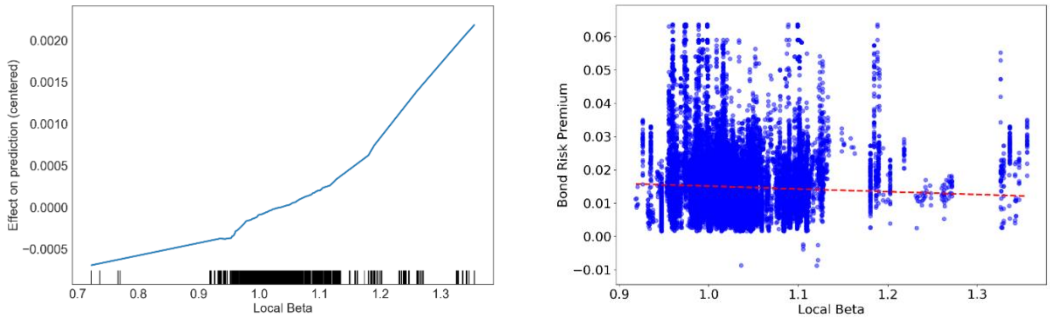
In general, for most variables, the ANN is able to pick up nonlinear relationships in the data. Only two variables, namely volume and bid-ask-spread, have a linear relationship with REIT bond risk premia. In addition, with the ALE plots, we can assess whether there is a positive or negative relationship across all variable values or whether the relationships are changing. It is evident that an ANN, together with ALE plots, can uncover nonlinearities that help to specify a stronger OLS in the next step. Appendices 3.C and 3.D show the ALE plots of all control variables and the corresponding univariate OLS.

Figure 3.6a shows the effect of the local beta factor, i.e. the risk of the local real estate market, on the risk premium prediction of REIT bonds. The relationship between the local beta and the REIT bond risk premia indicates that higher local real estate market risk is reflected in higher risk premia for the REIT bonds. We assume that this is because investors want to be compensated for the additional risk they take on when holding REIT bonds exposed to more volatile real estate markets, which could result in less predictable cash flows and asset values.

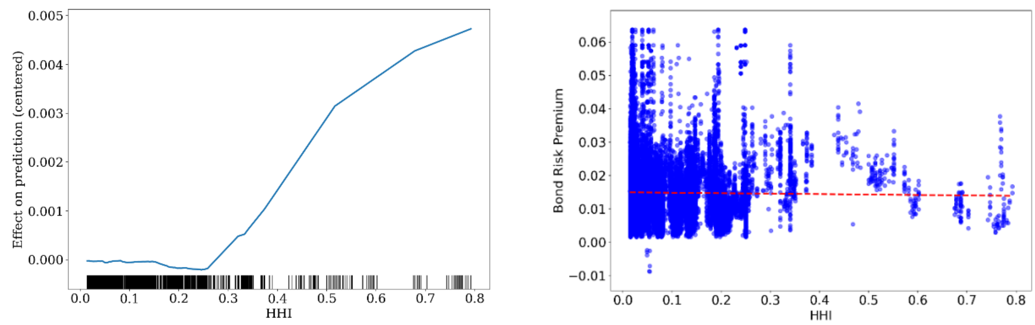
Figure 3.6b shows the effect of geographic concentration measured as HHI on the risk premia prediction of REIT bonds. In line with modern portfolio theory, which posits diminishing benefits from diversification, the relationship exhibits a clear nonlinear pattern. Starting from high concentration levels (i.e. high HHI), increased geographic diversification reduces predicted bond risk premia up to an HHI of around 0.25. Beyond this point, however, further diversification is associated with rising risk premia, suggesting that the costs of managing highly dispersed portfolios, such as increased complexity or reduced transparency, may outweigh the risk-reducing benefits.

Figure 3.6: ALE Plot and Univariate Regression of Local Beta and HHI

(a) Local Beta



(b) HHI



3.6.2 Optimized Regression Results

Based on the observed patterns, the baseline variables are transformed to higher degree terms. These polynomial transformations of all control variables in the OLS, based on the inflections of the ALE plots, can be seen in Appendix 3.E. Table 3.5 shows the regression summary for all model specifications. The coefficients are mostly in line with the shown relationship in the ALE plots in Figure 3.6 and Appendix 3.C and 3.D. Also, the control variables are in line with previous literature (e.g., default risk captured by market capitalization, see Lui (2021) and liquidity risk, see Longstaff et al. (2005)).

The results of Model 1 (the optimized OLS based on inflections in the ALE plots) show that local real estate market risk, i.e. the local beta, is statistically significant. It becomes evident that with an increase in real estate market risk, there is an increase in REIT bond risk premia. Thus, we can confirm that investors require higher bond risk premia to be adequately compensated for higher exposure to riskier local real estate markets. However, the magnitude of the local beta coefficient is smaller than that observed in the study of Zhu and Lizieri (2022) concerning REIT equity returns. This aligns with our theoretical argument that bondholders, due to their higher priority of claims are less sensitive to geographic risks compared to equity holders.

For robustness reasons, Model 2 shows that this positive relation between local real estate market risk and REIT bond risk premia is consistent across all REITs, irrespective of their exposure to riskier local real estate markets (high beta REITs, i.e. local beta above median) or more stable local real estate markets (low beta REITs, i.e., local beta below median). In monetary terms, for a typical \$500 million bond issuance for REITs in the high local beta group, an increase in local beta from the 25th to the 75th percentile translates into approximately \$295,711 to \$583,999 in additional annual interest costs, illustrating the tangible financial impact of local real estate market risk on REIT debt financing.

The analysis of Models 1 and 2 reveals a statistically significant negative relationship between the HHI and REIT bond risk premia, suggesting that greater geographic concentration (or lower diversification) corresponds with reduced risk premia across the entire dataset. However, the ALE plot in Figure 3.6b shows a structural break in the data around the value of an HHI of 0.25. To account for this observed change in the data, we specify Model 3, where the sample is divided into REITs with high geographic concentration (HHI above 0.25) and those with low geographic concentration (HHI below 0.25). The results show that increased geographic concentration for REITs with higher HHI relates to higher bond risk premia. Conversely, for REITs with lower HHI, increased geographic concentration is associated with reduced bond risk premia. This suggests that for more concentrated REITs, the advantages of geographic diversification, such as reduced earnings volatility, outweigh the associated information and monitoring costs, leading investors to require lower risk premia. In contrast, for more diversified REITs, the additional costs of further geographic diversification surpass its benefits, leading to higher required bond risk premia. This adds a public debt perspective to the discussion on the coined "diversification discount" found in previous literature for REIT value and other operating metrics (e.g., Feng et al., 2021; Hartzell et al., 2014; Huerta & Mothorpe, 2024; Ibrahim & Falkenbach, 2024). Ibrahim and Falkenbach (2024) find a REIT bond risk premium for geographic diversification, regardless of the REIT's level of diversification. Our finding that the effect of diversification depends on the given diversification level of a REIT is consistent with modern portfolio theory, which suggests that the benefits of diversification diminish as diversification increases (Markowitz, 1952). This nonlinear pattern may have been overlooked in prior studies on geographic diversification. To further validate the structural break in HHI, we perform a Chow test, which confirms a significant break at the HHI level of 0.25.

However, it is important to note that the effect size (0.48%) of geographic concentration on risk premia for REITs with high HHI is less pronounced than the effect size for REITs with lower HHI (1.71%). It seems that investors require a higher compensation for the costs of additional geographic diversification for REITs that are already well diversified (i.e. REITs with an HHI < 0.25) than they are willing to offer a REIT bond risk premia discount for geographic diversification for concentrated REITs (i.e. REITs with an HHI > 0.25). This new perspective reinforces the benefits of combining ML and traditional methods.

Since the effect of geographic diversification on risk premia appears to depend on the level of concentration, it implies that for REITs exposed to more volatile markets, diversification might influence bond costs differently than for REITs with a lower local beta. To explore this relationship more formally, Model 4 includes an interaction term between local beta and HHI. The interaction term yields a coefficient of 0.0191, indicating that the positive impact of local beta on bond risk premia is amplified in more concentrated markets. Contrary, this suggests that increased geographic diversification for REITs in high-risk markets may lead to significantly lower bond risk premia, effectively mitigating volatility-related concerns. This supports the hypothesis that REITs exposed to volatile markets benefit more from diversification and concentrating in a few areas becomes costly in terms of bond risk premia beyond a certain point. Conversely, in more stable markets, the same level of diversification might incur additional management costs and operational complexities, which could explain the inflection point for HHI at 0.25. In other words, while concentration alone might reduce risk premia initially, for REITs operating in more volatile markets, concentration beyond a certain point is associated with increased risk premia. This finding emphasizes the importance of maintaining an optimal balance in geographic diversification and risk market strategies.

Table 3.5: Regression Results – REIT Bond Risk Premium

	(1) Polynomial	(2) High-Low Beta	(3) High-Low HHI	(4) Interaction
$\beta_{i,t-1}^{REIT}$	0.0021***		0.0022***	0.0004*
	(0.001)		(0.001)	(0.001)
$High\ \beta_{i,t-1}^{REIT}$		0.0323***		
		(0.001)		
$Low\ \beta_{i,t-1}^{REIT}$		0.0321***		
		(0.001)		
HHI_{t-1}	-0.0015***	-0.0015***		-0.0205**
	(0.001)	(0.001)		(0.008)
High HHI_{t-1}			0.0048***	
			(0.001)	
Low HHI_{t-1}			-0.0171***	
			(0.001)	
$\beta_{i,t-1}^{REIT}$ * HHI_{t-1}				0.0191**
				(0.008)
Volume	1.477e-10**	1.469e-10**	1.461e-10**	-1.421e-10**
	(6.64e-11)	(6.64e-11)	(6.64e-11)	(6.64e-11)
Bond Price	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(5.84e-06)	(5.83e-06)	(5.82e-06)	(5.84e-10)
Coupon Rate	0.2421***	0.2435***	0.2401***	0.2428***
	(0.005)	(0.005)	(0.005)	(0.005)
Volume Weighted Yield	0.0485***	0.0485***	0.0486***	0.0485***
	(0.001)	(0.001)	(0.001)	(0.001)
Time to Maturity	5.849e-06***	5.731e-06***	5.929e-06***	5.875e-06***
	(5.26e-07)	(5.25e-07)	(5.26e-07)	(5.26e-07)
Credit Rating	0.0013***	0.0013***	0.0013***	0.0013***
	(9.05e-05)	(9.03e-05)	(9.04e-05)	(9.06e-05)
Call Status	-0.0023***	-0.0023***	-0.0024***	-0.0023***
	(0.000)	(0.000)	(0.000)	(0.000)
Market Cap	-0.0036***	-0.0037***	-0.0037***	-0.0036***
	(6.03e-05)	(6.07e-05)	(6.03e-05)	(6.03e-05)
Equity Return	0.0025***	0.0025***	0.0025***	0.0025***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.0073***	0.0074***	0.0073***	0.0075***
	(0.001)	(0.000)	(0.001)	(0.001)
Return on Assets	-0.0682***	-0.0694***	-0.0689***	-0.0679***
	(0.005)	(0.005)	(0.005)	(0.005)
Market-to-Book	8.17e-05	9.378e-05*	8.762e-05*	9.024e-05*
	(5.05e-05)	(5.06e-05)	(5.04e-05)	(5.07e-05)
Default Risk Spread	1.0788***	1.0781***	1.0803***	1.0789***
	(0.026)	(0.026)	(0.026)	(0.026)
IVOL	-0.1114***	-0.1112***	-0.1105***	-0.1114***
	(0.013)	(0.013)	(0.013)	(0.013)
Bond Zero Trading Days	-0.0049***	-0.0049***	-0.0049***	-0.0049***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Zero Trading Days	-0.0041***	-0.0042***	-0.0042***	-0.0041***
	(0.000)	(0.000)	(0.000)	(0.000)
Bid-Ask Spread	0.0869***	0.0868***	0.0870***	0.0864***
	(0.004)	(0.004)	(0.004)	(0.004)
Health Care	0.0019***	0.0021***	0.0019***	0.0019***
	(0.000)	(0.000)	(0.000)	(0.000)
Hotel & Resort	0.0063***	0.0063***	0.0063***	0.0061***
	(0.000)	(0.000)	(0.000)	(0.000)
Industrial	0.0021***	0.0021***	0.0020***	0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)

Table 3.5: Regression Results – REIT Bond Risk Premium (continued)

	(1) Polynomial	(2) High-Low Beta	(3) High-Low HHI	(4) Interaction
Office	0.0003	0.0003	0.0004	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
Residential	-0.0003	-0.0002	1.791e-05	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)
Retail	-0.0010***	-0.0009***	-0.0010***	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Specialized	0.0021***	0.0022***	0.0022***	0.0021***
	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes	Yes
Property Type FE	Yes	Yes	Yes	Yes
R^2	0.729	0.727	0.728	0.729

Notes: Dependent variable is the REIT bond yield spread in decimals (e.g., 0.012 = 1.2%). Standard errors are reported in parenthesis. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The variables Dividends, FFO, VIX, S&P 500, Unemployment Rate, Term Spread and GDP were excluded from the OLS for multicollinearity reasons (VIF values exceeded 10). To further ensure that multicollinearity is not affecting the standard errors, we also estimate the regressions without control variables while keeping the fixed effects. The results remain robust. All model specifications are based on the polynomial regression with variable transformations reported in Appendix 3.E.

3.6.3 Performance Evaluation of Applied Methods

Table 3.6 illustrates the performance indicators of the ANN and the OLS over the entire sample period. $OLS_{Baseline}$ represents the regression without any variable transformations (which is not displayed in the previous Table 3.5 and used here solely for performance comparison), while $OLS_{Polynomial}$ corresponds to Model 1 shown in Table 3.5 and includes polynomial transformations guided by the ALE plots. The results show that incorporating insights from the ALE plots improves the OLS model's fit, with R^2 increasing from 67.1% in the basic model to 72.9% in the polynomial specification. The ANN displays the highest explanatory power, with an R^2 value of 82.5%, reinforcing the value of using ML models to inform and enhance traditional econometric models such as an OLS.

Table 3.6: Performance Comparison of All Models

Metrics	$OLS_{Baseline}$	$OLS_{Polynomial}$	Δ $OLS_{Polynomial}$ / $OLS_{Baseline}$	ANN	Δ ANN/ $OLS_{Baseline}$
MSE	0.000026	0.000022	−15,4%	0.000015	−42,3%
MAE	0.0034	0.0032	−5,9%	0.0028	−17,6%
R^2	0.671	0.729	+8,6%	0.825	+23,0%

3.7 Conclusion

To the best of our knowledge, this study is the first to examine the relationship between local real estate market risk and REIT bond risk premia. The motivation behind our analysis is that REITs exposed to more volatile local real estate markets (i.e. REITs with a local beta above 1) should have more volatile asset values, thereby increasing default risk. As a result, we hypothesize that bondholders will demand higher risk premia from REITs with greater exposure to local market volatility and that this effect may differ from what is observed for equity holders, given bondholders' limited upside, priority of claims and heightened sensitivity to downside risk. We investigate whether these local asset-level risks, as well as geographic diversification, are reflected in the pricing of REIT bonds.

Our dataset includes 30,186 monthly observations of REIT bond risk premia from 2010 to 2023. To capture local market risk, we construct a local beta factor using REIT-level property data, which measures the sensitivity of local real estate markets to aggregate national real estate market shocks. Additionally, we quantify geographic concentration of REIT portfolios by calculating HHI values for each REIT.

This study makes several contributions to the literature on geographic characteristics as determinants of commercial real estate investment risk and return. Regarding our first research question, we find a local real estate market risk premium in REIT bonds. Investors demand higher compensation for REITs that are exposed to more volatile local markets. This positive relationship between local-market volatility and bond risk premia holds across the entire sample, both for REITs concentrated in high-volatility areas and for those operating mainly in more stable regions. This aligns with the notion of structural models of credit risk, such as Merton (1974), where increased asset volatility elevates the default risk perceived and priced by debt investors. As expected, the effect is less pronounced for REIT bonds compared to REIT equity, as shown by Zhu and Lizieri (2022) which can be explained by the difference in risk-return profiles and claim order in the capital structure between bondholders and shareholders.

Turning to our second research question, we reveal a more nuanced, nonlinear impact of geographic diversification on REIT bond risk premia, consistent with modern portfolio theory's assumption that diversification benefits only up to a certain threshold. For REITs with more concentrated portfolios, increased diversification is associated with lower bond risk premia, suggesting that the benefits of diversification, such as more stable cash flows, outweigh the potential costs related to information and monitoring. However, for REITs that are already well-diversified, further diversification leads to higher bond risk premia, indicating that the additional costs of diversification outweigh its benefits. This finding refines the concept of a geographic diversification discount in REIT bonds, as documented in prior research. We identify a turning point at an HHI concentration value of around 0.25, which marks the threshold where further diversification becomes less beneficial from a REITs perspective.

Finally, addressing our third research question, we reveal an important interaction effect: in more volatile markets (high local beta), higher geographic concentration (high HHI) leads to a disproportionately larger increase in bond risk premia. This interaction suggests that the combined effect of local market volatility and concentration amplifies risk, especially in high-risk environments.

Methodologically, we demonstrate the value of integrating non-parametric ML approaches, such as ANNs and ALE plots, to enhance traditional parametric models like OLS. By using ALE plots to visualize nonlinear relationships, we optimize the OLS model and achieve improved predictive performance, offering a methodological contribution that extends beyond the REIT bond literature and can be applied to other asset classes or contexts.

Understanding the link between fundamental location characteristics of commercial real estate and REIT bond risk premia provides valuable insights for REIT managers, investors and bond portfolio managers. For REIT managers, these findings offer a framework for optimizing geographic market allocations over the long term, with the aim of lowering the cost of future public debt issuances. While short-term portfolio restructuring in response to specific issuance conditions is generally not feasible due to asset illiquidity and transaction costs, strategic adjustments in acquisition, development and divestment decisions over time can shape geographic exposure in ways that benefit future financing costs. For investors, the results show that local real estate market risk is a material driver of REIT bond risk premia in the secondary market, providing an additional lens for credit risk assessment beyond firm-level financial metrics. Bond portfolio managers can leverage these insights to refine pricing models, improve investment decisions and enhance risk-adjusted returns.

3.8 References

Apley, D. W., & Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. *Journal of the Royal Statistical Society. Series B: Statistical Methodology*, *82*(4), 1059–1086. https://doi.org/10.1111/rssb.12377

Benefield, J. D., Anderson, R. I., & Zumpano, L. V. (2009). Performance differences in property-type diversified versus specialized real estate investment trusts (REITs). *Review of Financial Economics*, *18*(2), 70–79. https://doi.org/10.1016/j.rfe.2008.04.001

Bessembinder, H., Kahle, K. M., Maxwell, W. F., & Xu, D. (2009). Measuring abnormal bond performance. *The Review of Financial Studies*, *22*(10), 4219–4258. https://doi.org/10.1093/rfs/hhn105

Capozza, D. R., & Seguin, P. J. (1999). Focus, transparency and value: The REIT evidence. *Real Estate Economics*, *27*(4), 587–619. https://doi.org/10.1111/1540-6229.00785

Cheok, S. M. C., Sing, T. F., & Tsai, I.C. (2011). Diversification as a value-adding strategy for Asian REITs: A myth or reality? *International Real Estate Review*, *14*(2), 184–207. https://www.gssinst.org/irer/2020/04/28/diversification-as-a-value-adding-strategy-for-asian-reits-a-myth-or-reality

Demirci, I., Eichholtz, P., & Yönder, E. (2020). Corporate diversification and the cost of debt. *The Journal of Real Estate Finance and Economics*, *61*(3), 316–368. https://doi.org/10.1007/s11146-017-9645-9

Feng, Z., Pattanapanchai, M., Price, S. M., & Sirmans, C. F. (2021). Geographic diversification in real estate investment trusts. *Real Estate Economics*, *49*(1), 267–286. https://doi.org/10.1111/1540-6229.12308

Fisher, G., Steiner, E., Titman, S., & Viswanathan, A. (2022). Location density, systematic risk, and cap rates: Evidence from REITs. *Real Estate Economics*, *50*(2), 366–400. https://doi.org/10.1111/1540-6229.12367

Freybote, J. (2016). Real estate sentiment as information for REIT bond pricing. *Journal of Property Research*, *33*(1), 18–36. https://doi.org/10.1080/09599916.2016.1146791

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, *29*(5), 1189–1232. https://www.jstor.org/stable/2699986

Gospodinov, N., & Robotti, C. (2021). Common pricing across asset classes: Empirical evidence revisited. *Journal of Financial Economics*, *140*(1), 292–324. https://doi.org/10.1016/j.jfineco.2020.12.001

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, *33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Haran, M. E., Lo, D., McCord, M., Davis, P., & Lim, L. C. (2020). Impact of firm-level attributes on listed real estate company performance. *Journal of Property Investment & Finance*, *39*(4), 323–348. https://doi.org/10.1108/JPIF-03-2020-0030

Hartzell, J. C., Sun, L., & Titman, S. (2014). Institutional investors as monitors of corporate diversification decisions: Evidence from Real Estate Investment Trusts. *Journal of Corporate Finance*, *25*, 61–72. https://doi.org/10.1016/j.jcorpfin.2013.10.006

Huerta, D., & Mothorpe, C. (2024). The impact of property clustering on REIT operational efficiency and firm value. *The Journal of Real Estate Finance and Economics*, 71(1), 476-509. https://doi.org/10.1007/s11146-023-09973-w

Ibrahim, I., & Falkenbach, H. (2024). Diversification and cost of public debt for REITs: Evidence from the US. *Journal of Real Estate Portfolio Management*, *30*(1), 36–53. https://doi.org/10.1080/10835547.2023.2233348

Krämer, B., Nagl, C., Stang, M., & Schäfers, W. (2023a). Explainable AI in a real estate context – Exploring the determinants of residential real estate values. *Journal of Housing Research*, *32*(2), 204–245. https://doi.org/10.1080/10527001.2023.2170769

Krämer, B., Stang, M., Doskoč, V., Schäfers, W., & Friedrich, T. (2023b). Automated valuation models: Improving model performance by choosing the optimal spatial training level. *Journal of Property Research*, *40*(4), 365–390. https://doi.org/10.1080/09599916.2023.2206823

Liu, Y., & Wu, J. C. (2021). Reconstructing the yield curve. *Journal of Financial Economics*, *142*(3), 1395–1425. https://doi.org/10.1016/j.jfineco.2021.05.059

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance*, *60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

Loo, W. K. (2020). Predictability of HK-REITs returns using artificial neural network. *Journal of Property Investment & Finance*, *38*(4), 291–307. https://doi.org/10.1108/JPIF-07-2019-0090

Lorenz, F., Willwersch, J., Cajias, M., & Fuerst, F. (2023). Interpretable machine learning for real estate market analysis. *Real Estate Economics*, *51*(5), 1178–1208. https://doi.org/10.1111/1540-6229.12397

Lui, A. (2021). *Does size matter? Incorporating company size in credit risk assessment.* S&P Global Market Intelligence. https://www.spglobal.com/market-intelligence/en/news-insights/research/does-size-matter-incorporating-company-size-in-credit-risk-assessment

Lundberg, S., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Proceedings of the 31st International Conference on Neural Information Processing Systems*. https://dl.acm.org/doi/10.5555/3295222.3295230

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974

McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, *34*(4), 574–589. https://doi.org/10.1080/07350015.2015.1086655

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470. https://doi.org/10.2307/2978814

Ro, S., & Ziobrowski, A. J. (2011). Does focus really matter? Specialized vs. diversified REITs. *The Journal of Real Estate Finance and Economics*, *42*(1), 68–83. https://doi.org/10.1007/s11146-009-9189-8

Serrano, C., & Hoesli, M. (2007). Forecasting EREIT Returns. *Journal of Real Estate Portfolio Management*, *13*(4), 293–310. https://doi.org/10.1080/10835547.2007.12089784

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, *15*(56), 1929–1958. http://jmlr.org/papers/v15/srivastava14a.html

Tuzel, S., & Zhang, M. B. (2017). Local risk, local factors, and asset prices. *The Journal of Finance*, *72*(1), 325–370. https://doi.org/10.1111/jofi.12465

Wang, Y., Li, Y., Song, Y., & Rong, X. (2020). The influence of the activation function in a convolution neural network model of facial expression recognition. *Applied Sciences*, *10*(5), 1897. https://doi.org/10.3390/app10051897

Zhu, B., & Lizieri, C. (2022). Local beta: Has local real estate market risk been priced in REIT returns? *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-022-09890-4

3.9 Appendix

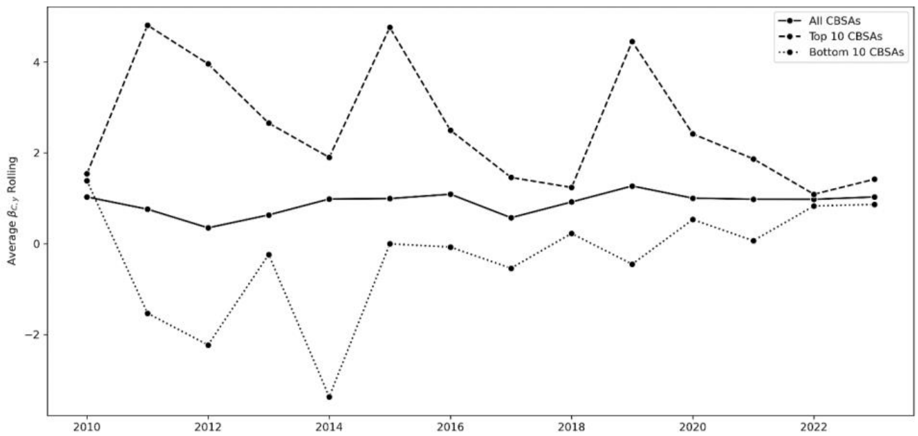
Appendix 3.A – Rolling Local Beta Construction and OLS Results

For robustness reasons, we additionally calculate a rolling local beta, denoted as $\beta_{c,y}^{REIT}$, which captures the local real estate market risk for CBSA c in year y. This is achieved by applying the regression specified in Equation (3.2) annually, yielding time-varying local betas for each CBSA:

$$\mathrm{r}_{\mathrm{c},(\mathrm{y}-1,\mathrm{y})}^{\mathrm{NPI}} - \mathrm{r}_{\mathrm{f},(\mathrm{y}-1,\mathrm{y})} = \alpha_{\mathrm{c,y}} + \beta_{\mathrm{c,y}}\left(\mathrm{MKT}_{(\mathrm{y}-1,\mathrm{y})}^{\mathrm{NPI}} - \mathrm{r}_{\mathrm{f},(\mathrm{y}-1,\mathrm{y})}\right) + \varepsilon_{\mathrm{c,y}}. \tag{3.A.1}$$

The Figure 3.7 below displays the average rolling $\beta_{c,y}^{REIT}$ for all CBSAs and for the ten top and bottom 10 CBSAs. While the average $\beta_{c,y}^{REIT}$ of all CBSAs is around 1 and therefore in line with the average of β_c, the top and bottom 10 CBSAs exhibit more extreme spreads ($\beta_{c,y}^{REIT}$ values > 4 and < -3) compared to the histogram in Figure 3.1. This is likely because the fixed beta (β_c) smooths out short-term property market volatility, leading to more stable coefficients. Moreover, the top 10 and bottom 10 CBSAs show more fluctuations compared to the overall average.

Figure 3.7: Rolling Local Beta



Notes: The figure plots the average rolling local beta over time. The figure is based on a rolling regression for every year. The top and bottom 10 CBSAs are identified based on the average value of all years of the rolling regression, then their yearly average is calculated.

The regression results are displayed in Table 3.7 on the next page. The results remain robust.

Table 3.7: Rolling Beta Regression Results

Variables	Rolling Beta Coefficients
$\beta_{i,y-1}^{REIT}$	0.0015*
	(6.67e-05)
HHI_{t-1}	-0.0019***
	(0.001)
Volume	1.477e-10**
	6.64e-11
Bond Price	-0.0003***
	(5.83e-06)
Coupon Rate	0.2438***
	(0.005)
Volume Weighted Yield	0.0485***
	(0.001)
Time to Maturity	5.794e-06***
	(5.25e-07)
Credit Rating	0.0014***
	(9.04e-05)
Call Status	-0.0023***
	(0.000)
Market Cap	-0.0037***
	(6.04e-05)
Equity Return	0.0025***
	(0.000)
Leverage	0.0077***
	(0.000)
Return on Assets	-0.0674***
	(0.005)
Market-to-Book	8.513e-05*
	(5.06e-05)
Default Risk Spread	1.0781***
	(0.026)
IVOL	-0.1116***
	(0.013)
Bond Zero Trading Days	-0.0049***
	(0.000)
Firm Zero Trading Days	-0.0042***
	(0.000)
Bid-Ask Spread	0.0865***
	(0.004)
Health Care	0.0018***
	(0.000)
Hotel & Resort	0.0060***
	(0.000)
Industrial	0.0022***
	(0.000)
Office	0.0003
	(0.000)
Residential	-0.0003
	(0.000)
Retail	-0.0010***
	(0.000)
Specialized	0.0021***
	(0.000)
Time FE	Yes
Property Type FE	Yes
R^2	0.728

Appendix 3.B – Hyperparameter Distributions

Tuning the hyperparameters is a crucial aspect in setting up the right network architecture, which are defined ex-ante and refer to the parameters regulating the model design. Hyperparameters being tuned in this study include the learning rate, the dropout rate, the number of hidden layers, lambda L2 and the multiple. Table 3.8 below displays the distribution of each hyperparameter. Every constellation of hyperparameters is fitted annually on the training data and subsequently applied to the validation set. We chose not to include the activation function in the hyperparameter search but use the ReLu function for each hidden layer. This is because the ReLu function is less likely to create a vanishing gradient problem and can be computed efficiently, which are major benefits compared to other activation functions (Wang et al., 2020).

Table 3.8: Neural Network Hyperparameter Search Spaces

Hyperparameter	Distribution
Hidden Layer	$U^d \sim [1, 4]$
Neuron Multiple	$U^d \sim [1,6]$
Lambda L2	$U^c \sim [0.000001, 0.01]$
Learning Rate	$U^c \sim [0.0001, 0.01]$
Dropout Rate	$U^c \sim [0.10, 0.40]$

Appendix 3.C – ALE Plots and Univariate Regressions of Continuous Variables

Figure 3.8: ALE Plots and Univariate Regressions of Continuous Variables

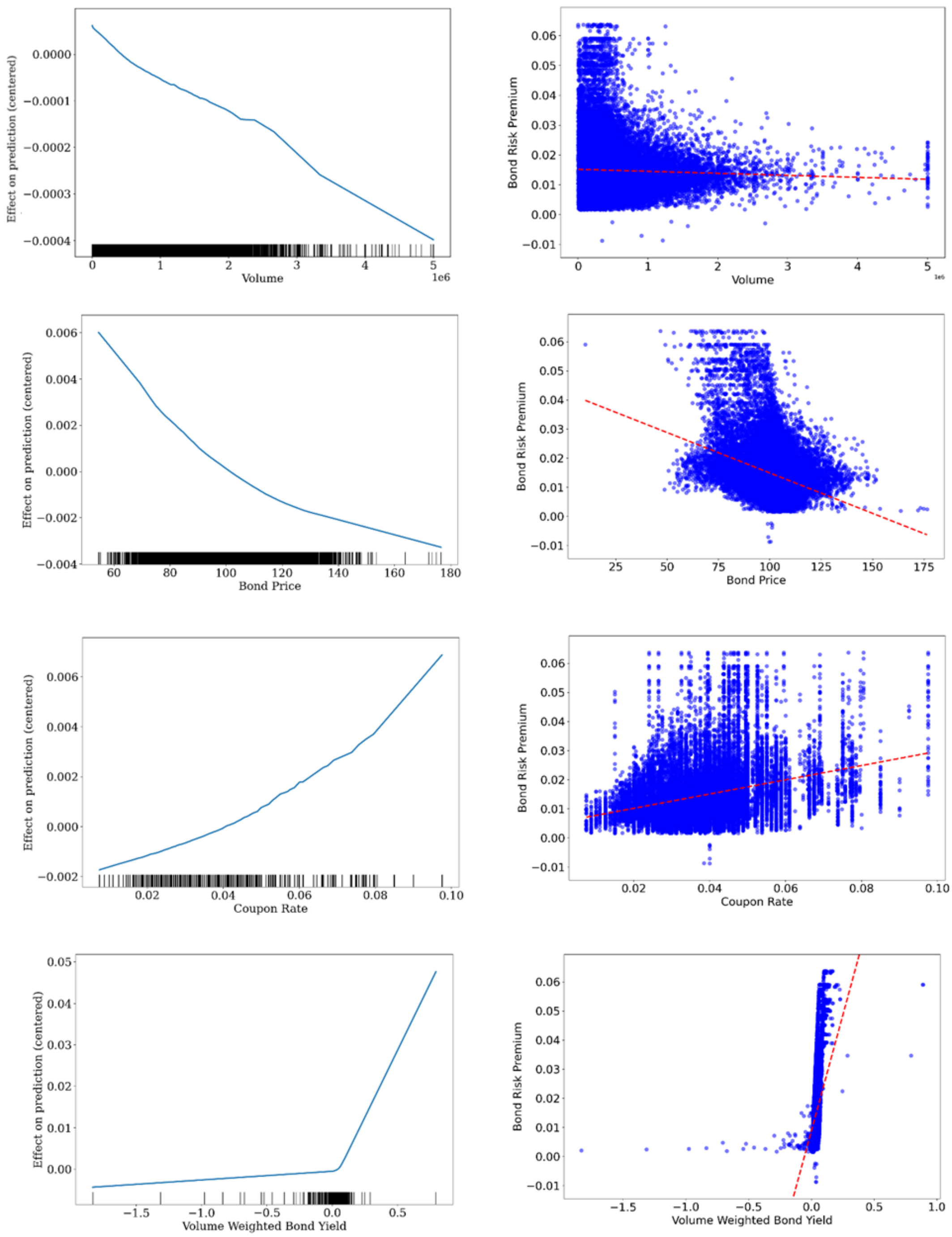


Figure 3.8: ALE Plots and Univariate Regressions of Continuous Variables (cont'd)

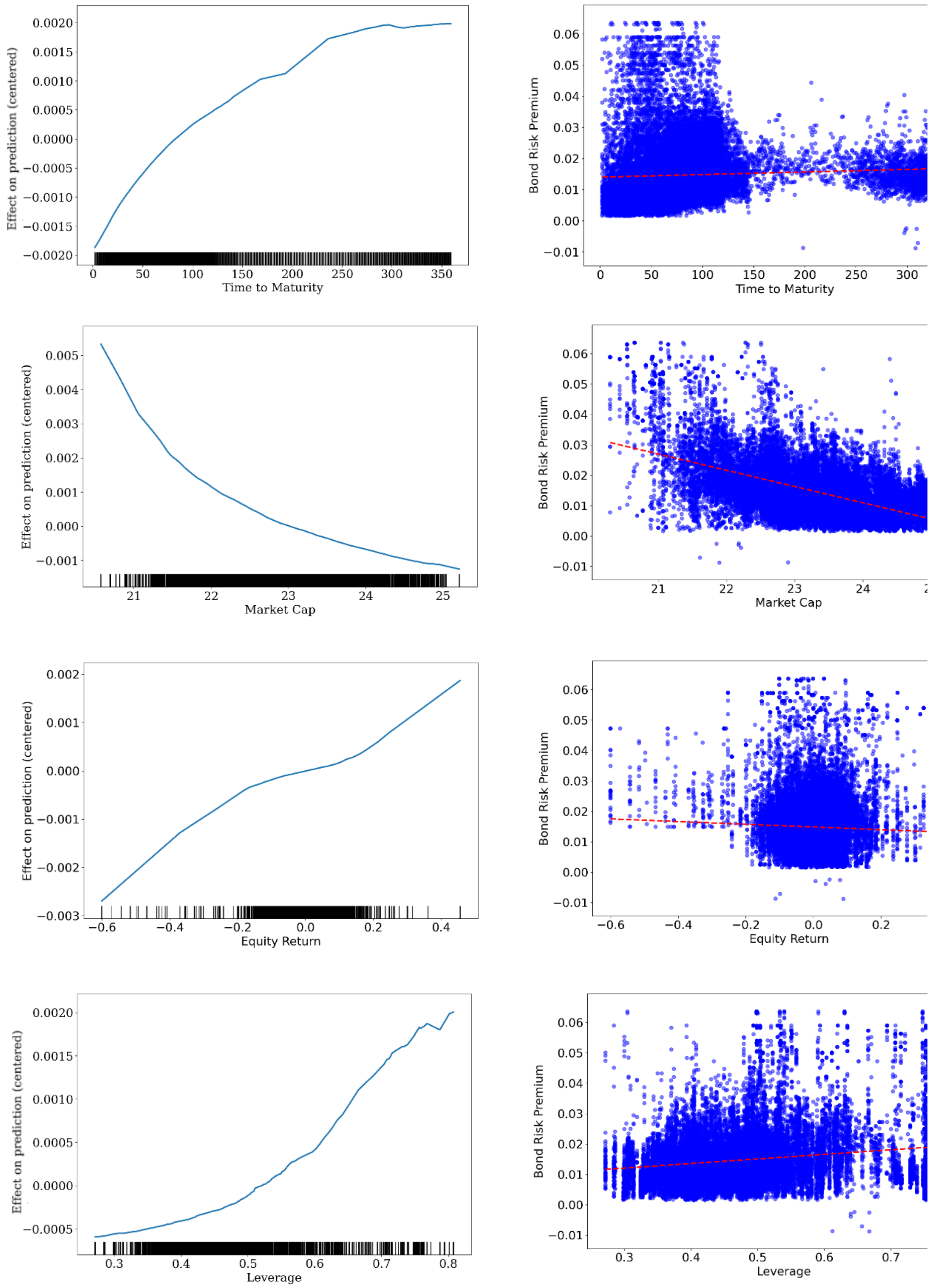


Figure 3.8: ALE Plots and Univariate Regressions of Continuous Variables (cont'd)

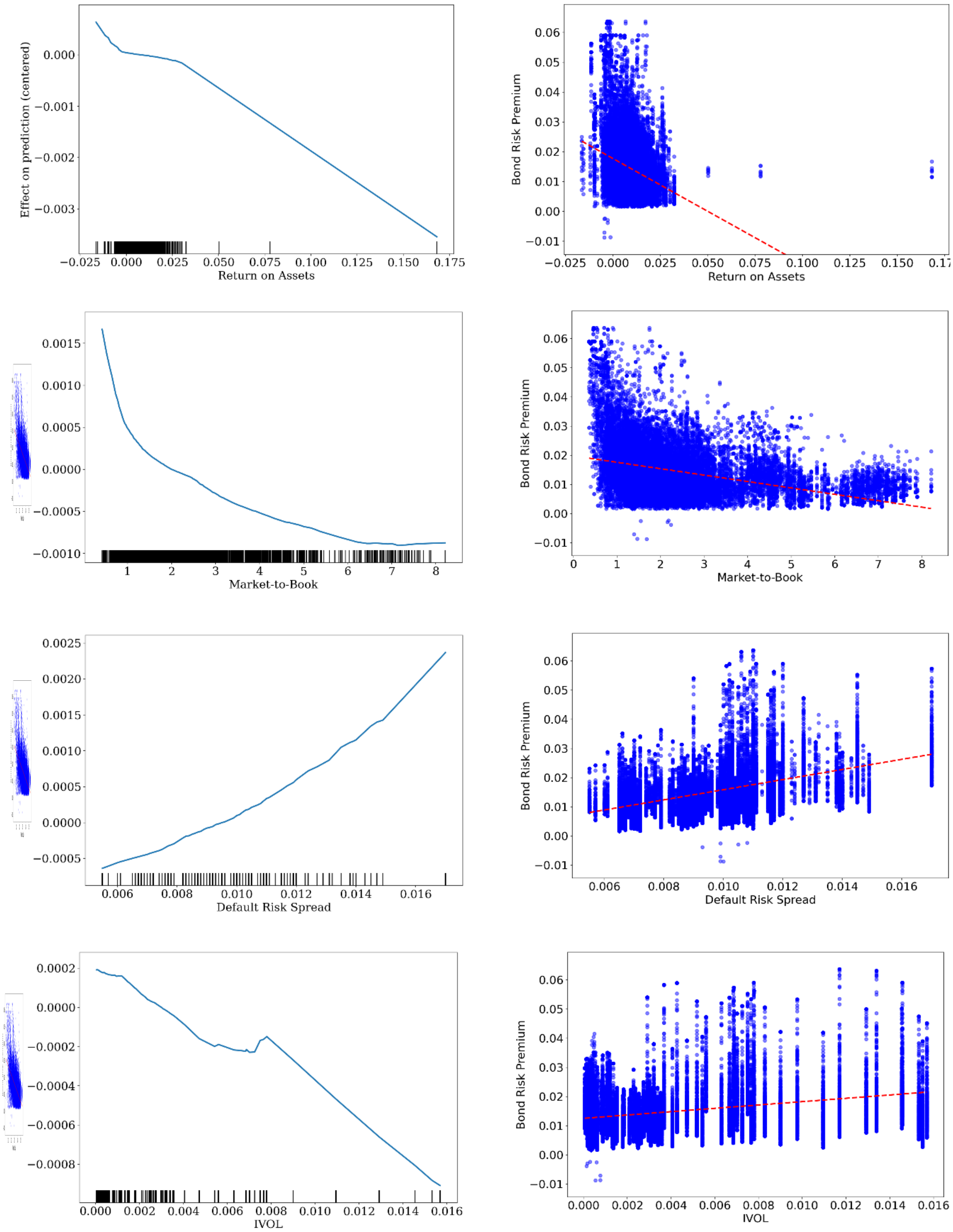
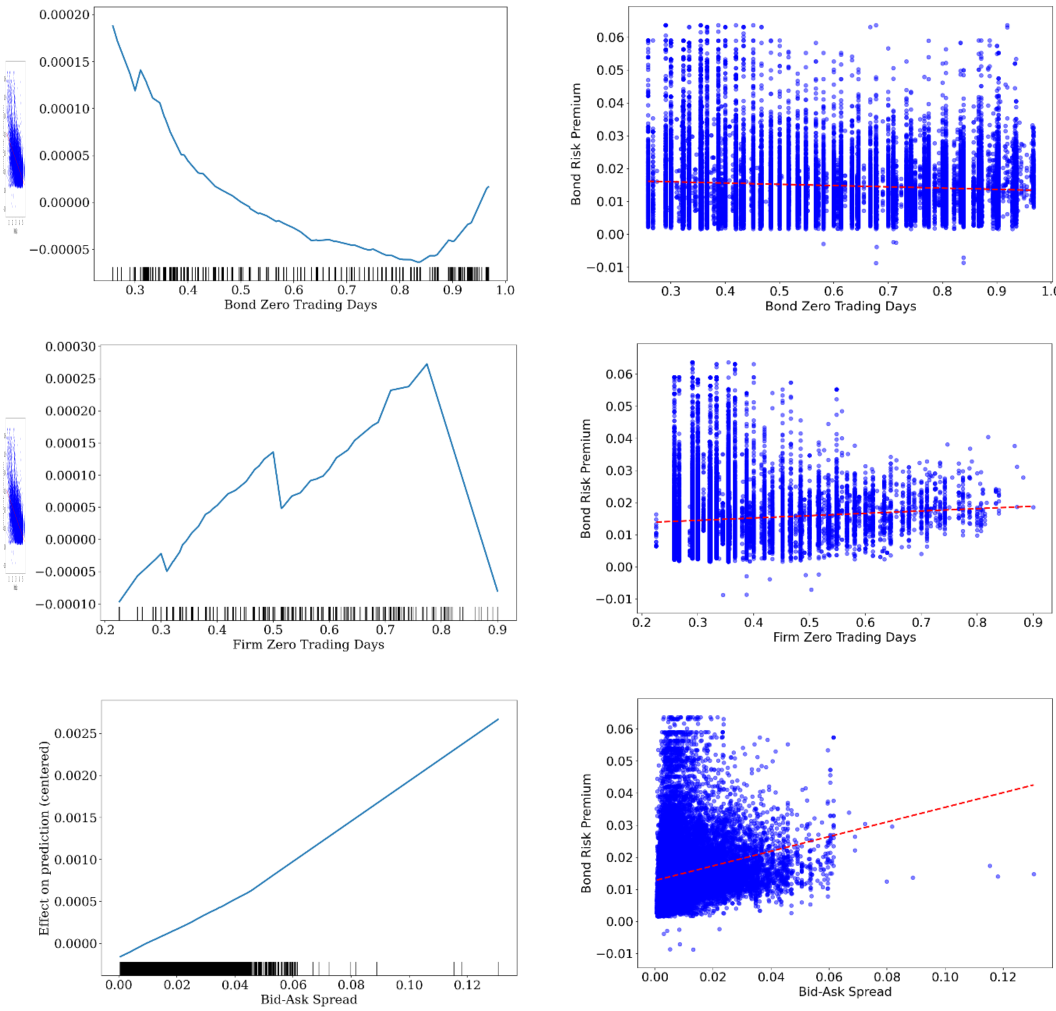


Figure 3.8: ALE Plots and Univariate Regressions of Continuous Variables (cont'd)



Appendix 3.D – ALE Plots and Univariate Regressions of Categorial Variables

Figure 3.9: ALE Plots and Univariate Regressions of Categorical Variables

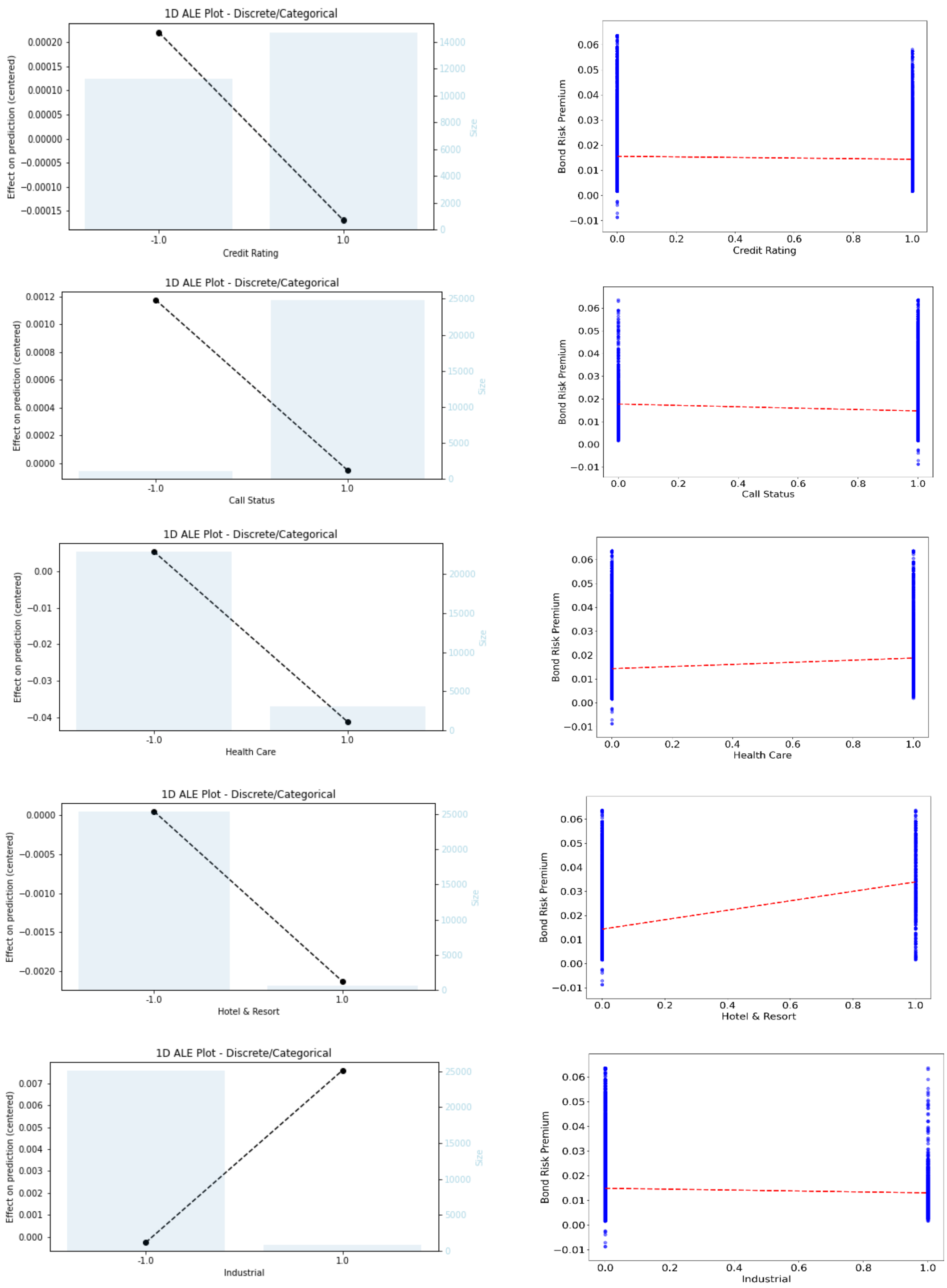
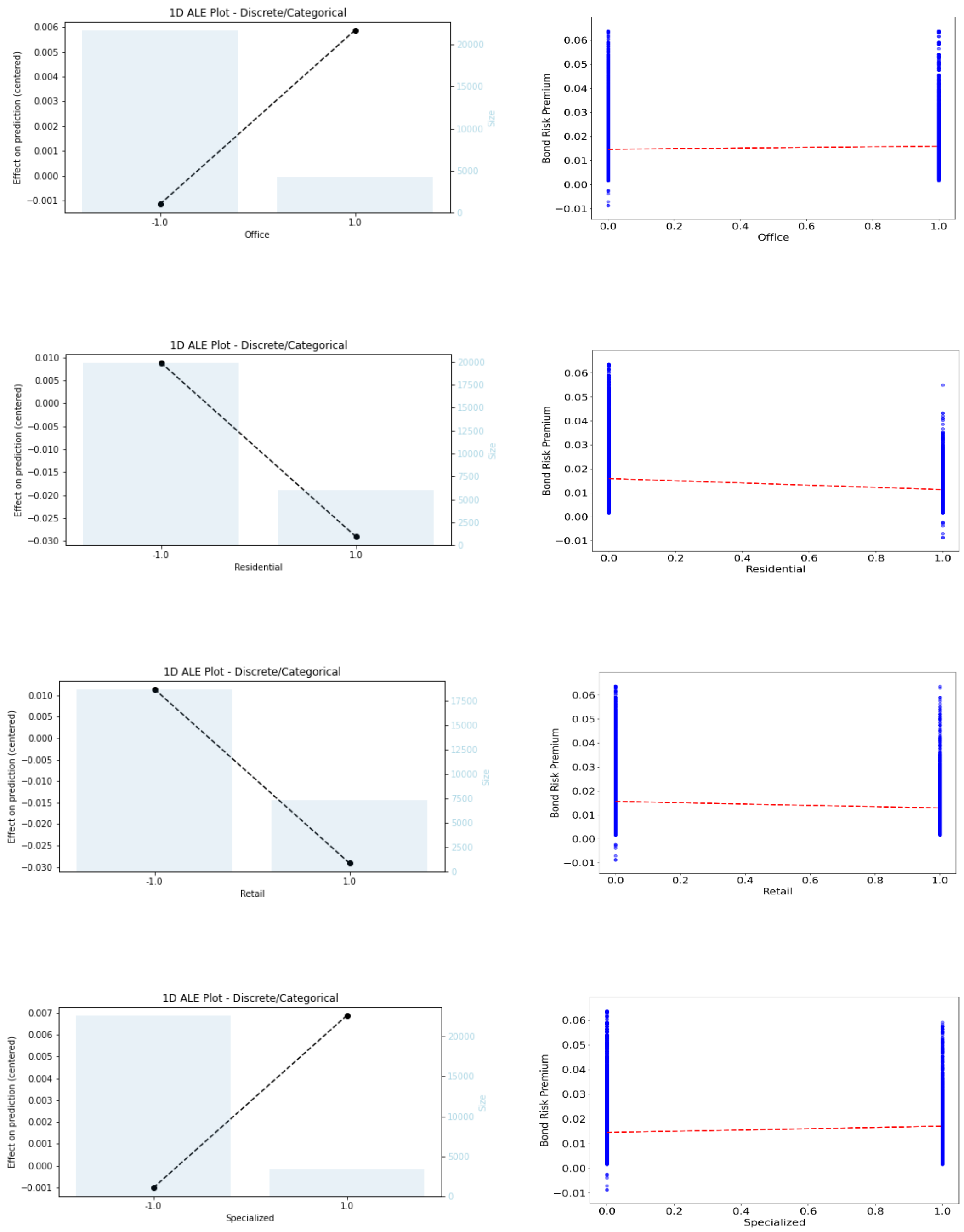


Figure 3.9: ALE Plots and Univariate Regressions of Categorical Variables (cont'd)



Appendix 3.E – Variable Transformations

Table 3.9: Variable Transformations to Optimize $\text{OLS}_{\text{Polynomial}}$

Variable	Transformation
$\beta_{i,t}^{REIT}$	Squared (^{2})
Volume	–
Bond Price	Squared (^{2})
Coupon Rate	Squared (^{2})
Volume Weighted Bond Yield	Squared (^{2})
Time to Maturity	Squared (^{2})
HHI	Cubed (^{3})
Market Cap	Squared (^{2})
Equity Return	Cubed (^{3})
Leverage	Squared (^{2})
Return on Assets	Cubed (^{3})
Market-to-Book	Cubed (^{3})
Default Risk Spread	Squared (^{2})
IVOL	Cubed (^{3})
Bond Zero Trading Days	Squared (^{2})
Firm Zero Trading Days	Power of (^{4})
Bid-Ask Spread	–

Notes: This table illustrates the transformations of each variable of the OLS regression based on the shape of the respective ALE plot. Dummy variables are not transformed due to their linear nature. The variables Dividends, FFO, VIX, S&P 500, Unemployment Rate, Term Spread and GDP were excluded from the OLS for multicollinearity reasons (VIF values exceeded 10), therefore, were also not transformed.

4 Do Real Estate Capital Markets Care About Physical Climate Risk?

4.1 Abstract

This study examines whether forward-looking, property-level physical climate risks are reflected in the pricing of U.S. Real Estate Investment Trust (REIT) equity and debt markets. We find that bond markets price flood, frost, drought, and wildfire risk, associated with increases in REIT bond risk premia. In contrast, equity markets predominantly price hurricane risk, which is negatively associated with REIT excess returns. These effects are driven by institutional investors, consistent with superior information access. We also find that flood risk premia increase when catastrophe-bond (CAT bond) insurance risk premia are elevated, indicating sensitivity to insurance market conditions, whereas hurricane risk premia do not display similar co-movement. While investors do not strongly differentiate between near- and long-term climate risk projections, risk premia tend to be somewhat larger at longer risk horizons. This study advances the literature on real estate and climate finance by providing novel evidence of hazard-specific, property-level physical climate risk pricing in REIT debt and equity markets.

Keywords: Physical Climate Risk, Real Estate Investment Trust, REIT, Commercial Real Estate, Capital Market, Climate Finance

4.2 Introduction

Advancing climate change is leading to more frequent and severe destructive weather events such as floods, storms, and droughts (see e.g., Ritchie & Roser, 2024; Shenoy et al., 2022). In 2024 alone, the economic costs of such events in the U.S. are estimated at $183 billion, with an inflation-adjusted annual compound growth rate of 22% over the past decade, according to data from the National Centers for Environmental Information (NOAA, 2025). Institutional investors increasingly recognize climate change as a material financial risk (Krueger et al., 2020). Yet, despite this growing awareness, a majority of finance professionals and academics believe that climate-related risks remain insufficiently reflected in asset prices (Stroebel and Wurgler, 2021).

Climate-related risks can be categorized into transition risks, arising from regulatory and policy responses to climate change, and physical risks, resulting from adverse effects of destructive weather events or long-term environmental changes on physical assets (Task Force on Climate-Related Financial Disclosures, 2017). While recent studies show that transition risk is increasingly priced by both public equity and debt markets (see e.g., Bolton & Kacperczyk, 2021, 2023; Hsu et al., 2023; Ramelli et al., 2021; Seltzer et al., 2025), physical climate risk, which is the focus of this study, appears to be largely ignored in capital markets (see e.g., Faccini et al., 2023; Hong et al., 2019). A key reason for this discrepancy may lie in challenges to measure physical climate risk (Hoehn et al., 2024; Robinson et al., 2022). Most empirical studies rely on text-based proxies, such as the frequency of climate-related terms in newspaper articles (Faccini et al., 2023) or impacts of past major destructive weather events (Brown et al., 2021; Hong et al., 2019). While such methods may capture market awareness or reactions, they do not directly measure asset-level physical climate risk expectations. Therefore, in this paper we use forward-looking physical climate risk data geocoded at the property level that quantifies the projected likelihood and intensity of categories of destructive weather events for each five-year interval between 2025 and 2100.[17]

The real estate sector is particularly vulnerable to physical climate risk due to the immobility of its assets, their high capital intensity, and the long-term nature of property investments. Prior studies have documented price discounts related to physical climate risk for both residential (see e.g., Contact et al., 2024; Fuerst & Warren-Myers, 2021; Issler et al., 2024; Kousky et al., 2020; Mueller et al., 2009; Pommeranz & Steininger, 2020) and commercial

[17] The data is based on the Climate Score Global methodology developed by Jupiter Intelligence, a U.S.-based firm specializing in physical climate risk analytics. Jupiter reports that its analytics are used operationally by approximately one-quarter of the world's largest financial institutions.

properties in the U.S. (see e.g., Addoum et al., 2024; Fisher & Rutledge, 2021; Sirmans et al., 2025).

However, while pricing impacts of physical climate risk have been shown at the asset level, the pricing transmission of property level risk exposure into capital markets, specifically the cost of debt and equity, remains largely underexplored. Real Estate Investment Trusts (REITs) offer a suitable empirical setting to analyze these transmission effects, since they account for $2.5 trillion of commercial real estate assets in 2025, a significant portion of U.S. commercial real estate (NAREIT, 2025). As publicly traded portfolios of immobile, income-generating assets, their financial performance is highly sensitive to property operability, insurability and occupancy. These factors may be negatively affected by the results of destructive weather events, namely physical damage, rising operating costs, or increased capital expenditures for resilience measures.

In addition, REITs also exhibit greater asset-level transparency than non–real estate corporations. They typically disclose the location and characteristics of their property portfolios to investors, making physical climate risk assessment more feasible. In contrast, non–real estate corporations often do not reveal the geographic distribution and operational importance of physical assets (i.e., offices and production facilities) as part of their complex supply chains, making it difficult for investors to assess business disruption risk and its financial implications from local destructive weather events (Hain et al., 2022).

This study analyzes the transmission of physical climate risk on the property level to the stock and bond markets by leveraging detailed asset-level physical climate risk data. Given the distinct risk-return profiles of stocks and bonds we are also interested in potential differences in the effect of physical climate risk on these securities. Not only do public debt holders have higher priority of claims than equity holders, but they are also primarily exposed to downside risk as their return is limited by fixed payments. This contrasts with equity holders who benefit from theoretically unlimited upside potential. Therefore, bondholders might price physical climate risk differently than equity holders.

We find that physical climate risks are priced in real estate capital markets, but the nature of the pricing differs between debt and equity markets and investor types. Specifically, we observe that flood, frost, and wildfire risks are positively associated with higher REIT bond risk premia, indicating that credit investors demand higher risk premia to compensate for exposure to these hazards. These effects are statistically significant and economically meaningful, with risk premia increasing by up to four percentage points for bonds issued by REITs with properties more exposed to high-risk areas. In contrast, in the REIT equity market, only hurricane risk is significantly priced by up to ten percentage points, and it is negatively related to excess equity returns, suggesting that higher hurricane exposure is associated with lower REIT performance. We further find that this effect is driven by institutional investors, who might be better equipped to assess and incorporate such risks into their investment decisions. Finally, we show that the time horizon does not materially affect pricing; equity investors do not differentiate strongly between near-term and long-term physical climate risks, although pricing of longer-term risks appears marginally more pronounced.

Our paper makes several contributions to the literature on climate and real estate finance. First, we use a more robust and science-based measure of physical climate risk by employing forward-looking, location-specific risk assessments used operationally by major global financial institutions rather than text-based proxies derived from news media. In doing so, our findings challenge earlier studies that rely on retrospective or text-based measures of physical climate risk (see e.g., Faccini et al., 2023) and align more closely with recent research using forward-looking, asset-level risk assessments (see e.g., Ling et al., 2024). Second, we add greater nuance to the analysis by distinguishing between multiple hazard types rather than relying on a single aggregated risk score or focusing on one hazard in isolation. Third, we provide a comprehensive perspective by jointly examining how physical climate risks are priced across real estate debt and equity capital markets, while also accounting for differences in time horizons and investor types.

The remainder of this paper is structured as follows. Section 4.3 reviews prior literature and introduces the guiding questions for our research. Section 4.4 introduces the physical climate risk measures and describes the dataset. Section 4.5 outlines the methodological approach. Section 4.6 presents and discusses the empirical results. Section 4.7 concludes.

4.3 Literature Review

The relationship between physical climate risk and asset prices has emerged as a rapidly expanding field of academic research. Within the real estate sector, this literature can be broadly classified into two distinct strands. The first and historically earlier strand focuses on the property level, examining the implications of physical climate risks for property valuation. More recently, a second strand has developed, investigating the effects of climate risk on real estate capital markets. The following review differentiates between these two strands and situates our study within this evolving body of research.

4.3.1 Physical Climate Risk in Real Estate and Capital Markets

There is broad literature on the effect of physical climate risk on residential real estate. It focuses on the relationship of house prices or mortgage rates and a single type of destructive weather event, such as hurricanes (see e.g., Contat et al., 2024), floods (see e.g., Fuerst & Warren-Myers, 2021; Pommeranz & Steininger, 2020; Zhang & Leonard, 2019) and wildfires (see e.g., Götz et al., 2024; Issler et al., 2024; Mueller et al., 2009). Most of these studies find a discount on house prices or increase in mortgage rates related to the specific physical climate hazard analyzed. Importantly, because they evaluate price effects after a disaster has already occurred, their measure of physical climate risk is inherently backward-looking. One notable exception is the literature on flood risk that uses flood zone designations, which capture the ex-ante probability of future flooding rather than solely observed damages. In contrast, empirical evidence on the effects of physical climate risk in commercial real estate markets remains limited. Addoum et al. (2024) analyze the effect of physical climate risk exposure on commercial real estate transaction prices following Hurricane Sandy and find a significant negative trend for coastal commercial properties following the disaster, even in locations not directly affected by the hurricane. Similarly, Fisher and Rutledge (2021) find that commercial real estate exhibits damped property values and total returns up to five years after a hurricane event. Here as well, the focus lies on ex-post market responses to realized physical climate shocks.

A number of studies have investigated how physical climate risks are associated with different asset classes traded on capital markets. Using current drought conditions as their measure of physical climate risk, Huynh et al. (2020) state that exposure to droughts increases a firm's cost of equity. Using textual analysis of Reuter news articles with respect to climate-specific terms, Faccini et al. (2023) find that their text-based measure for physical climate risk is not priced in U.S. equities. Similarly, studies on corporate bonds fail to detect pricing effects of physical climate risk (Mastouri et al., 2022). However, municipal bond markets show clearer patterns of climate risk pricing, particularly in relation to sea-level rise (Goldsmith-Pinkham et al., 2023; Painter, 2020).

Two studies are particularly relevant to our research as they investigate the impact of physical climate risks on REIT stock performance. Feng et al. (2024) analyze the influence of physical climate risk exposure on U.S. REITs and document that greater portfolio exposure correlates with reduced cash flows, firm value, and stock returns. Their measure of physical climate risk is backward-looking and based on abnormal temperature deviations at the county level using publicly available NOAA data, which offers a valuable first-order approximation, though at a comparatively coarse spatial and hazard-specific resolution. Ling et al. (2024) distinguish between backward-looking disaster exposure and a forward-looking aggregated climate risk score. They find that REIT excess stock returns decline following disaster events, and that forward-looking risk is negatively associated with REIT valuation (measured by Tobin's Q) only when amplified by media attention.

4.3.2 Hypothesis Development

In contrast to prior literature, that adopts an aggregate forward-looking climate risk score, our approach operates at the individual hazard level. Building on prior work, we focus on five destructive weather hazards, namely flood, frost, hurricane, drought, and wildfire, within a unified empirical framework for the real estate bond and equity markets. These hazards are selected because they represent direct and locally observable physical manifestations of climate change that have been shown to affect asset values through property damage and operational disruption. We deliberately exclude broader temperature-based measures (e.g., heat stress) due to their high correlation with multiple hazards, which would introduce multicollinearity and hinder reliable hazard-specific inference. Aggregating all hazards into a single score may obscure the distinct spatial and temporal patterns of individual hazard types. For example, hurricanes are concentrated in coastal regions and develop over an extended period, whereas wildfires predominantly occur inland and often emerge abruptly. Treating these fundamentally different phenomena with a homogeneous risk measure may misrepresent their true pricing effects leading to misleading inferences. Based on this reasoning we hypothesize that different hazard types show different statistical and economic significances.

To better understand the behavior of equity investors we address two additional research questions that further explore the pricing mechanisms and heterogeneity within the equity market response. Additional analysis investigates whether the composition of the equity investor base affects the pricing of physical climate risks in REITs. This hypothesis is motivated by prior studies indicating that ownership structure, and especially institutional ownership, is linked to variations in financial performance, including lower borrowing costs and reduced valuation discounts (e.g., Gilstrap et al., 2022; Hartzell et al., 2014). We are also interested how different time horizons for the physical climate risk projections are priced differently by investors. Therefore, our study is guided by the following research questions:

1. To what extent does exposure to specific property-level physical climate risks influence REIT bond risk premia, and do the effects differ across hazard types?

2. To what extent does exposure to specific property-level physical climate risks influence REIT equity excess returns, and do the effects differ across hazard types?

2.1 Does equity investor composition (institutional vs. retail) affect the extent to which physical climate risks are priced?

2.2 Do REIT equity investors price physical climate risk projections differently depending on the assumed time horizon (current, 5, 15, or 30 years)?

In summary, existing research on physical climate risk in real estate has mainly focused on property-level effects on asset values. However, little is known about how specific physical hazards are priced across real estate debt and equity markets using forward-looking, property-level data. This study addresses this gap by examining how distinct climate hazards, including flood, frost, hurricane, drought, and wildfire, are reflected in REIT bond and equity pricing. It also explores whether investors differentiate between near-term and long-term risk horizons and whether institutional and retail investors price these risks differently.

4.4 Data

We examine how forward-looking physical climate risks are priced in real estate capital markets by analyzing U.S. REITs' equity and public debt data. This study therefore uses two datasets: one covering the REIT equity market and the other the REIT public debt market. Both contain identical measures of forward-looking physical climate risk, but differ in their dependent variables and in the set of control variables, reflecting the structural characteristics of each market. The construction and sources of all variables are detailed in the following section.

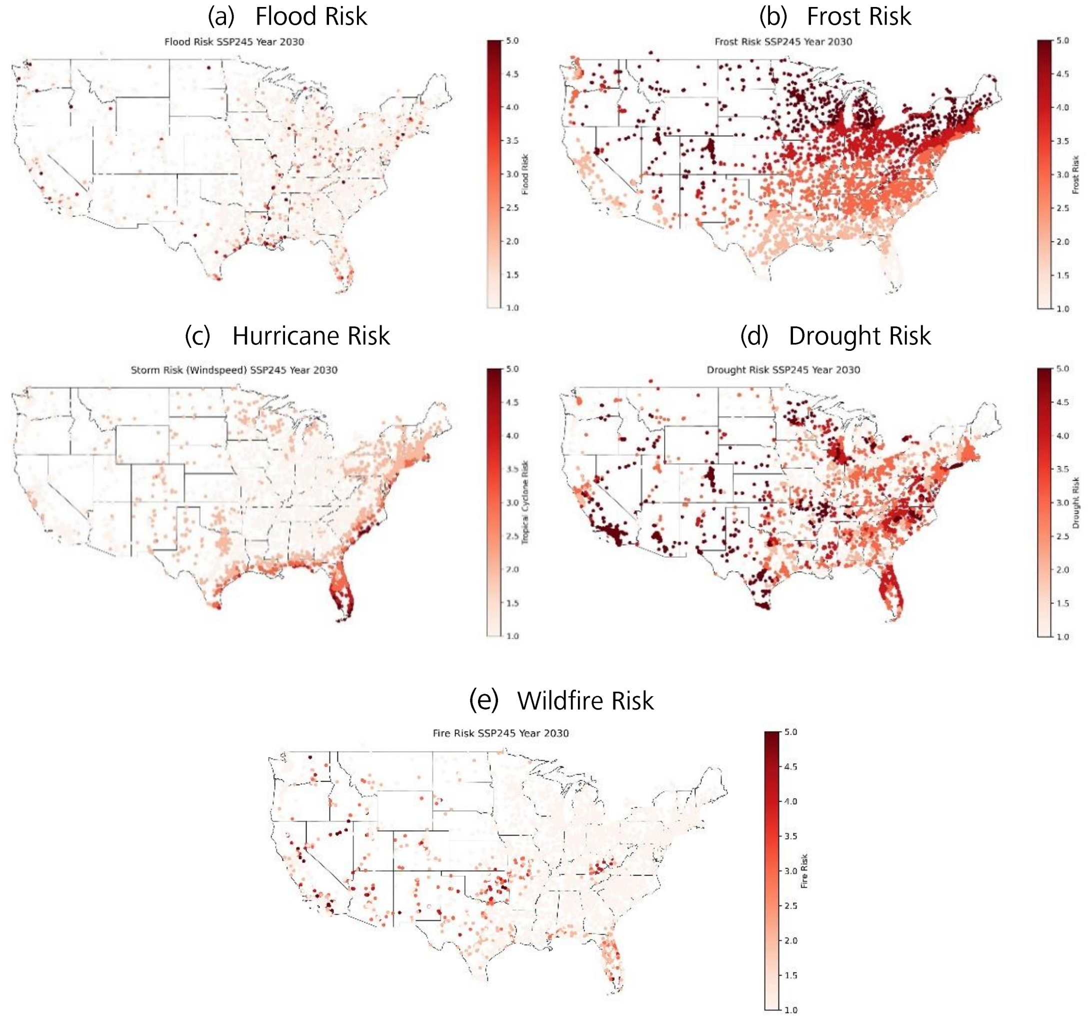
4.4.1 Forward-Looking Physical Climate Risk Data

Our analysis draws on forward-looking physical climate risk data from Jupiter Intelligence, a U.S.-based climate analytics provider. We use Jupiter's 2025 release, which provides projected risk scores for each REIT property location at five-year intervals from 2025 to 2100. The dataset covers several physical hazards, i.e., flood, frost, hurricane, drought, and wildfire, at the level of individual property coordinates. Property locations and REIT holding periods are obtained from S&P Capital IQ Pro. The projections evolve only slowly over time, as they are based on long-term climate model scenarios that are updated infrequently.[18] Figure 4.1 displays the raw physical climate-risk scores of REIT properties in our sample for the year 2030. These risk scores are based on peril metrics that are translated into five risk tiers from 1 (lowest) to 5 (highest). See Appendix 4.A for more information on these peril metrics. The spatial heterogeneity of these risks is evident; for example, frost risk is more pronounced in the northern United States, while hurricane risk is more prevalent along the southern and eastern coasts. The procedure used to aggregate property-level risk exposures to the REIT level is described in Appendix 4.B.

The underlying climate projections used by physical climate risk analytics providers such as Jupiter Intelligence are based on outputs from the Coupled Model Intercomparison Project (CMIP), a coordinated set of global climate models maintained under the Intergovernmental Panel on Climate Change (IPCC). The current so called CMIP6 provides standardized simulations of the Earth's climate system, which serve as the foundation for forward-looking hazard projections. These simulations are combined with Shared Socioeconomic Pathways (SSPs), which describe alternative climate futures up to 2100 based on social, economic, and technological trends. In this study, we use the SSP2-4.5 "middle-of-the-road" scenario, characterized by moderate socio-economic development, limited sustainability efforts, and gradual reductions in greenhouse gas emissions. Under SSP2-4.5, CO_2 emissions rise slightly until around 2040 and then decline slowly, insufficient to meet the Paris Agreement's 2 °C target. Thereby, this scenario is a conservative outlook, not being overly optimistic but also not overly pessimistic. Hazard projections from Jupiter are provided on a grid of forecast horizons $k \in 2025, 2030, \ldots, 2100$.

[18] Following Ling et al. (2024), we assume that forward-looking physical climate risk projections can be applied retrospectively; in our study, the 2025 release is used for 2021 – 2024. The projections rely on the Coupled Model Intercomparison Project (CMIP), a coordinated set of climate models under the Intergovernmental Panel on Climate Change (IPCC), which are updated roughly every six years (e.g., CMIP5 in 2015, CMIP6 in 2021). Since model updates and underlying physical processes change slowly, applying the 2025 release to the immediately preceding years is appropriate.

Figure 4.1: Forward-Looking Physical Climate Risk



Notes: Forward-looking physical climate risk scores of individual REIT properties for the year 2030.

4.4.2 Dependent and Control Variables

The dependent variable for the debt market specification is the REIT bond risk premium, while for the equity market specification it is the REIT equity excess return. REIT bond yields are obtained from the Trade Reporting and Compliance Engine (TRACE) database of the Financial Industry Regulatory Authority (FINRA), and U.S. Treasury yields are sourced from the dataset of Liu and Wu (2021). The REIT bond risk premium is calculated as the yield spread between each bond's yield to maturity and the corresponding maturity-matched Treasury yield, using data from 2021 – 2023. REIT equity excess returns are derived from total returns obtained from S&P Capital IQ Pro for the 2021 – 2024 period. In addition, we include a comprehensive set of control variables to account for established determinants of pricing in both capital markets covering REIT fundamentals, equity market performance and liquidity, bond market liquidity, macroeconomic factors, insurance market conditions and coastal exposure. Equity returns, company financials, and stock liquidity measures are obtained from S&P Capital IQ, bond liquidity data from TRACE and macroeconomic indicators from the FRED-MD database (McCracken & Ng, 2016). For indicators reported at the MSA level, such as GDP and unemployment, we aggregate values to the REIT level using the respective property ownership shares within each MSA. All variables are described in Table 4.3, and summary statistics for the debt and equity market are presented in Table 4.1 and Table 4.2, respectively.

Table 4.1: Summary Statistics of Bond Market Variables

Variable	Unit	Mean	Median	SD	Min	Max
Bond Risk Premium	Decimal	0.012	0.011	0.011	-0.032	0.053
Flood Risk	Index	0.242	0.174	0.221	0.000	1.513
Frost Risk	Index	1.548	1.629	0.586	0.000	3.000
Hurricane Risk	Index	0.669	0.727	0.389	0.000	4.031
Drought Risk	Index	2.226	2.171	0.463	0.000	4.022
Fire Risk	Index	0.107	0.108	0.095	0.000	0.460
Cat Bond Insurance RP	Percentage	2.455	2.625	2.293	0.018	5.431
Near Coast	Percentage	21.682	22.140	17.145	0.000	100.000
Term Spread	Decimal	-0.021	-0.022	0.035	-0.066	0.015
MSA Unemployment	Decimal	0.041	0.036	0.009	0.035	0.061
MSA GDP	USD	21,878.65	21,851.13	456.361	20,990.54	22,679.26
HHI	Integer	-0.146	-0.081	0.195	-1.000	-0.263
S&P 500 Return	Index	4,229.074	4,345.370	295.658	3,850.520	4,685.050
Market Capitalization	Mio. USD (log)	23.300	23.393	0.959	20.892	25.533
FFO	USD	5.164	3.967	3.470	0.500	14.900
Leverage	Decimal	0.479	0.478	0.123	0.286	0.768
Equity Return	Decimal	0.012	0.017	0.136	-0.345	0.350
Dividends	USD	3.212	2.474	2.213	0.040	9.020
Market to Book	Integer	1.992	1.758	1.083	0.410	6.155
Return on Assets	Decimal	0.008	0.008	0.007	-0.012	0.032
Bid Ask Spread	Decimal	0.008	0.005	0.009	0.001	0.051
Zero Trading Days	Decimal	0.310	0.300	0.048	0.258	0.533

As coastal U.S. markets differ systematically from inland areas, e.g., in terms of local GDP, housing prices and hurricane exposure, we control for coastal proximity. We calculate great-circle distances from each property to the nearest coastline and define coastal exposure as properties located within 20 km (approx. 12.4 miles) of the coast, in line with literature on U.S. coastal climate risk (Murfin & Spiegel, 2020; Wu & Kim, 2024). Quarterly REIT-level shares of coastal exposure are then computed based on this threshold. We also include the catastrophe (CAT) bond insurance risk premium sourced from Artemis.bm to capture changes in the market price of extreme weather event risk, which may affect investors' perception of physical climate risks.

Table 4.2: Summary Statistics of Equity Market Variables

Variable	Unit	Mean	Median	SD	Min	Max
Excess Return	Decimal	-0.022	-0.019	0.179	-0.962	1.067
Flood Risk						
Current	Index	1.226	1.169	0.238	1.000	2.500
5 YRS	Index	1.229	1.174	0.239	1.000	2.500
15 YRS	Index	1.243	1.177	0.286	1.000	3.000
30 YRS	Index	1.261	1.182	0.317	1.000	3.000
Frost Risk						
Current	Index	2.884	2.972	0.813	1.000	5.000
5 YRS	Index	2.831	2.926	0.778	1.000	4.923
15 YRS	Index	2.731	2.900	0.736	1.000	4.923
30 YRS	Index	2.642	2.826	0.733	1.000	4.923
Hurricane Risk						
Current	Index	1.636	1.577	0.468	1.000	5.000
5 YRS	Index	1.641	1.591	0.469	1.000	5.000
15 YRS	Index	1.652	1.609	0.468	1.000	5.000
30 YRS	Index	1.678	1.642	0.462	1.000	5.000
Drought Risk						
Current	Index	3.092	3.095	0.767	1.000	5.000
5 YRS	Index	3.097	3.105	0.766	1.000	5.000
15 YRS	Index	3.092	3.098	0.759	1.000	5.000
30 YRS	Index	3.040	3.043	0.763	1.000	5.000
Wildfire Risk						
Current	Index	1.098	1.059	0.135	1.000	2.000
5 YRS	Index	1.099	1.059	0.135	1.000	2.000
15 YRS	Index	1.102	1.063	0.136	1.000	2.000
30 YRS	Index	1.104	1.069	0.138	1.000	2.000
Cat Bond Insurance RP	Percentage	3.088	4.496	2.306	0.018	5.431
Near Coast	Decimal	0.217	0.108	0.277	0.000	1.000
Return on Assets	Decimal	0.017	0.019	0.078	-1.291	1.258
Leverage	Decimal	0.416	0.382	0.179	0.031	0.973
FFO	USD	132,222	59,893	213,156	-779,959	1,896,639
HHI	Integer	-0.245	-0.127	0.298	-1.000	-0.008
Market Capitalization	Mio USD (log)	8758	2901	15586	2	124557
Dividends	USD	-90,298	-33,501	156,370	-2,718,800	512
Risk-Free Rate	Decimal	0.032	0.044	0.023	0.000	0.055
Market Beta	Percentage	0.942	0.986	0.632	-6.963	3.023
Size Factor SMB	Percentage	1.084	1.098	0.840	-2.172	5.127
Value Factor HML	Percentage	0.205	0.262	0.817	-5.603	2.415
Profitability Factor RMW	Percentage	0.688	0.679	0.781	-2.279	4.746
Investment Factor CMA	Percentage	0.933	0.781	1.353	-2.794	10.180
MSA GDP	USD	1,212,151	106,4405	64,5702	81,276	3,392,762
Trading Volume	USD	1,289,796	845,081	1,761,494	8	24,134,000

Table 4.3: Variable Descriptions

Variable		Description
Dependent Variable		
RP	Bond Risk Premium	Difference between the yield to maturity of the REIT bond and the maturity matched Treasury yield to maturity
ER	Excess Return	Difference between the REIT equity return and the 3-month Treasury rate
Physical Climate Risk Scores		
FLOOD	Flood Risk	Depth of water from flooding (combined fluvial, coastal and pluvial) for an event with a 100-year return period
FROST	Frost Risk	The number of days per year the temperature is at or below temperature threshold (0 °C)
HURRICANE	Hurricane Risk	Expected 1-minute sustained wind speed (in km/hr) experienced with a 100-year return period. This includes tropical cyclones but no tornados
DROUGHT	Drought Risk	Ratio of demand for water to supply of water. High water stress values are an indicator of drought in a region
FIRE	Wildfire Risk	Mean annual probability of wildfire with the potential to cause loss, either originating in or passing through the cell the asset is located within
Insurance Market		
CAT	Catastrophe Bond	Catastrophe Bond Insurance Risk Premium
REIT Fundamentals		
ROA	Return on Assets	Net income divided by total assets
LEV	Leverage	Sum of long-term debt and short-term debt divided by shareholder's equity
FFO	Funds from Operations	Cash flow from operations
HHI	Geographic Diversification	Geographic diversification of REIT properties across the MSAs
Coastal Proximity		
COAST	Proximity to Coast	Share of properties in REIT portfolio in close proximity to coastline (<20 km)
REIT Stock Performance		
SIZE	Market Capitalization	Natural logarithm of market capitalization
MB	Market to Book	Market value of equity divided by book value of equity
DIV	Dividends	Distribution of a REIT's earnings to its shareholders
RET	Equity Return	Monthly REIT-level equity return
Fama-French Factors		
BETA	Market beta	Excess return of the broad market portfolio over a risk-free rate
SMB	Size	Excess return of small-cap stocks over large-cap stocks
HML	Value	Excess return of stocks with high book-to-market ratios (value stocks) over those with low ratios (growth stocks)
RMW	Profitability	Excess return of highly profitable firms over less profitable firms
CMA	Investment	Excess return of conservative-investing firms over aggressive-investing firms
Equity Market		
SP500	S&P 500 Return	Return of the S&P 500 composite index
Macroeconomic Environment		
UNEMP	Unemployment	Property-weighted unemployment rate of MSAs a REIT is invested in
GDP	GDP	Property-weighted GDP of MSAs a REIT is invested in
TS	Term Spread	10-Year Treasury rate minus 3-Month Treasury Bill
Bond Liquidity		
FZEROT	Firm Zero Trading Days	Percentage of days in a month on which no outstanding bond of a REIT was traded
BIDASK	Bid-Ask-Spread	Monthly mean of the difference in the average daily bid and ask prices of each bond
Equity Liquidity		
VOL	Volume	Daily traded volume of a REIT's stock

4.5 Methodology

Consistent with the use of separate datasets for the real estate debt and equity markets, we employ different empirical approaches to reflect the characteristics of each market. For the REIT bond market, a fixed effects panel regression captures how property-level physical climate risks affect bond risk premia over time. For the REIT equity market, the Fama–MacBeth two-step regression identifies whether these risks are systematically priced in equity excess returns. The next sections outline the methods for the debt and equity market specifications, respectively.

4.5.1 Debt Market Specification: Panel Regression

For the debt market specification, we first align bond maturities with the appropriate forward-looking climate risk horizon, matching each bond b to the climate risk forecast year closest to its contractual maturity m_b. The corresponding forecast horizon is denoted by k_b. For each quarter t, the REIT-level exposure to hazard h at horizon k_b is then assigned to the bond issued by REIT $i(b)$. This maturity-matching procedure ensures that each bond's climate exposure reflects the expected physical hazard risk over its effective investment horizon, providing a consistent basis for analyzing how physical climate risks affect REIT bond spreads.

For each bond b with maturity year m_b, we align it with the nearest available forecast horizon $fh \in FH = \{2025, 2030, \dots, 2100\}$ by selecting

$$k_b = \arg\min_{fh \in FH} |fh - m_b|. \tag{4.1}$$

We then assign to each bond–quarter observation the corresponding REIT-level climate exposure for hazard h at the matched horizon:

$$BondExp_{bt}^{(h)} = \mathrm{REITExp}_{\mathrm{i(b),t}}^{(\mathrm{h,k_b})}. \tag{4.2}$$

Subsequently, we estimate the effects of physical climate risks on REIT bond risk premia using a fixed effects panel regression at the bond–quarter level. The model relates each bond's yield spread over a maturity-matched treasury benchmark to the REIT's climate risk exposure, while controlling for a broad set of REIT-specific and market-level variables. Let $\mathrm{BondRiskPremium_{bt}}$ denote the quarterly bond risk spread for bond b of REIT $i(b)$ in quarter t, the regression is

$$\mathrm{BondRiskPremium_{bt}} = \beta_h \, \mathrm{BondExp_{bt}^{(h)}} + \gamma' X_{bt} + \alpha_b + \tau_{y(t)} + \upsilon_{q(t)} + \varepsilon_{bt}, \tag{4.3}$$

where X_{bt} includes macroeconomic, liquidity, and firm fundamentals. Non-stationary or skewed variables enter in first (log-)differences and stationary variables in levels. Bond fixed effects (α_b) control for time-invariant bond characteristics, while quarter (τ_t) and year (υ_y) fixed effects capture time shocks. Statistical inference is based on two-way clustered (bond × quarter) and Driscoll–Kraay HAC standard errors to address potential cross-sectional and temporal dependence (Cameron et al., 2011; Driscoll & Kraay, 1998). Model diagnostics include heteroskedasticity tests, information criteria (AIC/BIC), within-R^2, and checks for multicollinearity and outlier sensitivity.

4.5.2 Equity Market Specification: Fama-MacBeth Regression

We examine whether physical climate risks are systematically priced in REIT equity markets using the Fama–MacBeth two-step regression framework (Fama & MacBeth, 1973). This method first estimates REIT-specific exposures to systematic risk factors and then relates REIT equity excess returns to these exposures and to physical climate risk characteristics in each cross section, averaging the resulting coefficients over time.

Step 1: Time-series estimation of factor loadings. In the first step, we estimate rolling 36-month factor loadings for each REIT using the monthly Fama–French five-factor model (Fama & French, 2015). These loadings capture the sensitivity of each REIT's excess returns to common systematic risk factors, namely the market excess return (MKT), the size factor (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor (CMA), following the Fama–French five-factor model. SMB measures the return spread between small and large firms, HML between high and low book-to-market firms, RMW between firms with robust versus weak operating profitability, and CMA between firms that invest conservatively versus aggressively. Formally, for REIT i in month m,

$$R_{i,m}^{\mathrm{ex}} = \alpha_i + \beta_i^{\mathrm{mkt}}\,\mathrm{MKT_m} + \beta_i^{\mathrm{smb}}\,\mathrm{SMB_m} + \beta_i^{\mathrm{hml}}\,\mathrm{HML_m} + \beta_i^{\mathrm{rmw}}\,\mathrm{RMW_m} + \beta_i^{\mathrm{cma}}\,\mathrm{CMA_m} + u_{i,m}, \tag{4.4}$$

where $R_{i,m}^{\mathrm{ex}}$ denotes the excess return of REIT i in month m (over the risk-free rate); $\mathrm{MKT_m}$, $\mathrm{SMB_m}$, $\mathrm{HML_m}$, $\mathrm{RMW_m}$, and $\mathrm{CMA_m}$ are factor returns; $\beta_i^{\mathrm{mkt}}, \beta_i^{\mathrm{smb}}, \beta_i^{\mathrm{hml}}, \beta_i^{\mathrm{rmw}}, \beta_i^{\mathrm{cma}}$ are the corresponding factor loadings; α_i is an intercept while $u_{i,m}$ equals the error term. The equation is estimated over a rolling window of 36 months. The estimated betas are then mapped to quarters by taking the last month in the quarter (alternatively, the within-quarter average) and are included as one-quarter-lagged characteristics in the cross-sectional regressions.

Step 2: Cross-sectional regression of returns on risk factors. In the second step, we estimate unweighted OLS cross-sectional regressions of REIT excess returns ($R_{i,t}^{\text{ex}}$) on hazard exposures and control variables for each quarter t:

$$R_{i,t}^{\text{ex}} = a_t + \sum_{h \in \mathcal{H}} \sum_{k \in \mathcal{K}} \pi_t^{(h,k)} \, Z_{i,t}^{(h,k)} + \gamma_{\beta,t}^{\top} \widehat{\beta_{i,t}} + \delta_t{}' C_{i,t} + \varepsilon_{i,t}, \tag{4.5}$$

where i indexes REITs and t calendar quarters; h and k index hazards and forecast horizons (years), respectively; $Z_{i,t}^{(h,k)}$ are REIT–quarter exposures constructed from asset-level scores via asset-class median-centering and min–max scaling (Appendix 4.B); we do not maturity-match on the equity side but evaluate the full time horizon. $\widehat{\beta_{i,t}}$ denotes the one quarter lagged factor loadings derived from Equation (4.4), whereas $C_{i,t}$ contains additional firm- and market-level controls.

To ensure stable estimation, we remove predictors with near-zero cross-sectional variation, enforce a minimum coverage filter, address multicollinearity via an adaptive variance–inflation routine, and require a minimum effective sample size $N_t \geq \max\{N_{min}, K_{\text{eff}} + K_{\text{buffer}}\}$. Statistical inference follows Fama-MacBeth: we report Newey-West HAC t-statistics for the time-series mean of the quarterly cross-sectional coefficients, using four lags (Newey & West, 1987).

To assess ownership-structure heterogeneity, we split the sample at the median institutional ownership share, classifying REITs with above-median institutional ownership as institutionally dominated and those below as retail dominated, and re-estimate Equation (4.5) for each subsample.[19]

4.6 Results

We first report the effect of physical climate risk on REIT bond risk premia. Next, we explore the effect of physical climate risk on REIT equity excess returns, controlling for Fama French Factors. In addition, we show results for different risk time horizons and after splitting the data set by REIT ownership structure.

4.6.1 Evidence from the Real Estate Debt Market

Table 4.4 presents the results of the panel regressions examining how different types of forward-looking physical climate risks are reflected in REIT bond risk premia. The findings

[19] The median is employed as a non-parametric cutoff, as it (i) yields balanced subsamples in each cross-section, thereby preserving power in Fama–MacBeth estimation; (ii) is robust to tails and outliers in ownership; and (iii) is invariant to monotone rescaling.

indicate that investors differentiate across hazard types, suggesting that not all physical risks are equally priced in real estate debt markets.

Flood risk emerges as a consistently positive and statistically significant predictor of REIT bond risk premia across all model specifications. This indicates that REITs with higher flood exposure, whether from river, coastal, or flash flooding, are perceived as riskier, prompting investors to demand higher yields. Economically, moving from minimal to extreme flood risk (risk score of 0 to 1) is associated with a 2.9–4.5 percentage point increase in bond spreads. This aligns with evidence of flood-induced price discounts in property markets (e.g., Fuerst & Warren-Myers, 2021; Pommeranz & Steininger, 2020; Yi & Choi, 2020) and extends it to the debt side of public real estate capital markets. Frost risk is likewise positive and statistically significant across all specifications. Although the magnitude is smaller, moving from the lowest to the highest frost risk exposure corresponds to roughly a 1.0 – 1.2 percentage point increase in the REIT bond risk premium. This finding implies that investors account for cold-weather extremes as operational risks that may affect income stability and maintenance costs.

Hurricane risk does not exhibit a statistically significant relationship with REIT bond risk premia, suggesting that this specific hazard may be less relevant in pricing REIT debt, possibly due to geographic diversification or insurance mechanisms captured in the CAT insurance risk spread. In earlier specifications, hurricane exposure appeared statistically significant; however, once we include a coastal proximity control the coefficient collapses to insignificance, indicating that the prior association was driven by coastal location rather than hurricane risk per se and that, in our preferred specification, hurricane exposure has no stand-alone effect on REIT bond yield spreads. Drought risk shows a positive but slightly weaker statistically significant association with REIT bond risk premia in Model 1. The coefficient indicates that moving from minimal to extreme drought exposure is linked to an increase of about 1.1 percentage points in the bond risk premium. This may reflect concerns about water scarcity, higher operating costs, and potential property devaluations in drought-prone regions. Wildfire risk also exhibits a positive and statistically significant association with REIT bond spreads in Model 3. A shift from low to high wildfire exposure corresponds to an approximate 4.8 percentage point increase in risk premia. This result underscores growing investor concern about wildfire-related disruptions and complements evidence from housing and mortgage markets showing similar pricing effects (Issler et al., 2024; Götz et al., 2024). The CAT bond insurance risk premium, a proxy for aggregate market-wide physical climate risk perception, is also positively and significantly associated with REIT bond risk premia. This suggests that shifts in broader climate risk sentiment affect real estate credit spreads even for REITs with limited direct exposure, indicating a transmission channel from systemic climate risk perception to REIT debt pricing. Overall, the results demonstrate that several physical climate risks, particularly flood, frost, and wildfire, are incorporated into REIT bond pricing, whereas hurricane risk is not.

Table 4.4: Panel Regression Results – REIT Bond Risk Premium

	Model 1	Model 2	Model 3
Flood Risk	0.045***	0.034***	0.029**
	(0.011)	(0.012)	(0.012)
Frost Risk	0.018***	0.011***	0.015***
	(0.005)	(0.004)	(0.005)
Hurricane Risk		0.003	
		(0.005)	
Drought Risk	0.011*		
	(0.007)		
Wildfire Risk			0.048**
			(0.024)
Cat Bond Insurance Risk	0.002***	0.002***	0.002***
Premium	(2.56E-04)	(2.54E-04)	(2.56E-04)
Near Coast	-0.001***	-0.001***	-0.001***
	(1.83E-04)	(2.00E-04)	(2.85E-04)
Term Spread	-0.193***	-0.190***	-0.183***
	(0.034)	(0.034)	(0.033)
MSA Unemployment Rate	8.88E-05***	9.33E-05***	9.86E-05***
	(2.76E-05)	(2.80E-05)	(2.79E-05)
MSA GDP	-5.42E-08***	-5.55E-08***	-6.29E-08***
	(1.19E-08)	(1.14E-08)	(1.20E-08)
HHI	0.016	0.016*	0.020*
	(0.009)	(0.009)	(0.010)
S&P 500 Return	-9.07E-06***	-9.00E-06***	-8.60E-06***
	(1.13E-06)	(1.13E-06)	(1.12E-06)
Market Capitalization	0.005*	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
FFO	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Leverage	0.015	0.016*	0.018**
	(0.010)	(0.010)	(0.009)
Equity Return	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Dividends	-0.002***	-0.002***	-0.002***
	(4.56E-04)	(4.43E-04)	(4.27E-04)
Market to Book	-0.002***	-0.002***	-0.002***
	(4.89E-04)	(4.87E-04)	(4.76E-04)
Return on Assets	-0.105***	-0.107***	-0.100***
	(0.020)	(0.020)	(0.019)
Bid Ask Spread	0.001	0.001	0.002
	(0.011)	(0.011)	(0.011)
Zero Trading Days	0.009**	0.009**	0.009**
	(0.004)	(0.004)	(0.004)
Constant	0.037	0.077***	0.086***
	(0.033)	(0.017)	(0.017)
Time Fixed Effects	Yes	Yes	Yes
Bond Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.814	0.814	0.815

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.6.2 Evidence from the Real Estate Equity Market

Table 4.5 reports the results of the Fama–MacBeth regressions for REIT equity excess returns. The findings indicate that only hurricane risk is significantly priced in REIT equity markets. Across all forecast horizons, higher hurricane exposure is associated with lower excess returns, even after controlling for coastal proximity and other firm and market factors. Following Ferson and Harvey (1999), we study the time-series behavior of the quarterly Fama–MacBeth hazard prices by regressing the quarter-(t) price $(\widehat{\pi_t}(h))$ on the CAT-bond insurance risk premium. Flood risk exhibits pronounced state dependence, whereas hurricane risk does not. The risk premium for flood risk rises significantly in periods when CAT bond insurance risk premia are wide, i.e. when catastrophe reinsurance capital is limited. However, the risk premium for hurricane risk does not with in line with catastrophe bond markets. Overall, it seems that equity markets directly and persistently price hurricane risk, while flood risk is priced conditionally, it becomes more expensive for investors in states of insurance-capital stress. Further information on this evidence is provided in Appendix 4.C.

Turning to the control variables, the coefficients align well with theoretical expectations. REITs with higher FFO deliver higher excess returns, reflecting the advantages operational efficiency and greater liquidity. The positive and significant market beta confirms that systematic risk is compensated, consistent with the CAPM framework. Overall, the results suggest that real estate equity markets selectively price physical climate risks, with investors responding primarily to acute, high-impact perils such as hurricanes. This contrasts the bond market, where multiple physical hazards command a premium.

Effect of REIT Ownership Structure: Institutional and Retail Investors

A plausible explanation for the heterogeneous pricing of physical climate risks lies in differences between institutional and retail investor behavior. Institutional investors, such as pension funds, insurers, and asset managers, are often regarded as the "informed" segment of financial markets. Operating under fiduciary duties and equipped with analytical resources, they might be better positioned to assess and incorporate the financial implications of climate exposures into asset valuations. Retail investors, by contrast, typically face information and resource constraints. Their investment decisions tend to rely more on sentiment or short-term performance signals rather than systematic risk assessments. While they may respond to salient climate-related events covered in the media, they are less likely to consistently price longer-term physical risks. Consequently, higher institutional ownership should be associated with more accurate recognition and pricing of climate-related exposures, whereas retail-dominated ownership structures may underestimate such risks.

Table 4.5: Fama-MacBeth Regression Results – REIT Equity Excess Return

	(1) Current	(2) 5 YRS	(3) 15 YRS	(4) 30 YRS
Flood Risk	-0.009	-0.004	0.008	0.005
	(0.025)	(0.024)	(0.022)	(0.026)
Frost Risk	0.009	-0.002	0.001	0.019
	(0.019)	(0.022)	(0.013)	(0.015)
Hurricane Risk	-0.089***	-0.085**	-0.105***	-0.100***
	(0.027)	(0.027)	(0.029)	(0.030)
Drought Risk	0.003	0.004	0.008	-0.005
	(0.023)	(0.023)	(0.024)	(0.017)
Wildfire Risk	-0.013	-0.019	-0.032	-0.039
	(0.064)	(0.065)	(0.063)	(0.055)
Near Coast	0.010	0.009	0.006	0.010
	(0.008)	(0.008)	(0.006)	(0.007)
Market Risk Factor Beta	0.058**	0.059**	0.059**	0.059**
	(0.020)	(0.020)	(0.021)	(0.021)
Size Factor SMB	0.020	0.020	0.020	0.020
	(0.012)	(0.012)	(0.012)	(0.012)
Value Factor HML	-0.033	-0.033	-0.034	-0.033
	(0.020)	(0.020)	(0.020)	(0.019)
Profitability Factor RMW	-0.017	-0.017	-0.016	-0.017
	(0.020)	(0.020)	(0.021)	(0.021)
Investment Factor CMA	-0.031	-0.031	-0.032	-0.032
	(0.020)	(0.020)	(0.020)	(0.020)
GDP	-2.36E-08	-2.13E-08	-2.05E-08	-2.42E-08
	(1.29E-08)	(1.28E-08)	(1.32E-08)	(1.21E-08)
HHI	-0.040**	-0.041**	-0.040**	-0.048**
	(0.017)	(0.017)	(0.016)	(0.016)
Market Capitalization	0.141***	0.140***	0.142***	0.142***
	(0.040)	(0.039)	(0.039)	(0.039)
FFO	0.003**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	-0.055	-0.055	-0.056	-0.055
	(0.040)	(0.040)	(0.040)	(0.040)
Dividends	3.92E-08	4.19E-08	4.14E-08	4.01E-08
	(2.99E-08)	(3.15E-08)	(2.80E-08)	(2.65E-08)
Return on Assets	0.023	0.019	0.026	0.035
	(0.209)	(0.207)	(0.203)	(0.211)
Trading Volumes	1.51E-05	1.48E-05	1.55E-05	1.67E-05
	(9.68E-06)	(9.78E-06)	(9.20E-06)	(9.60E-06)
Constant	-0.139**	-0.138**	-0.137**	-0.138**
	(0.048)	(0.048)	(0.048)	(0.047)
Adj. R^2	0.482	0.484	0.479	0.477

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4.6: Fama-MacBeth Regression Results by Ownership Split – REIT Excess Return

	Institutional Ownership				Retail Ownership			
	(1) Current	(2) 5 YRS	(3) 15 YRS	(4) 30 YRS	(1) Current	(2) 5 YRS	(3) 15 YRS	(4) 30 YRS
Flood Risk	0.074**	0.074**	0.063**	0.059**	0.019	0.032	0.060	0.113
	(0.024)	(0.024)	(0.026)	(0.023)	(0.055)	(0.054)	(0.108)	(0.089)
Frost Risk	-0.016	-0.021	-0.013	-0.007	0.067*	0.059	0.027	0.035
	(0.021)	(0.022)	(0.015)	(0.016)	(0.035)	(0.036)	(0.036)	(0.044)
Hurricane Risk	-0.118***	-0.115***	-0.131***	-0.138***	-0.222	-0.258	-0.365	-0.135
	(0.031)	(0.033)	(0.041)	(0.035)	(0.216)	(0.226)	(0.207)	(0.162)
Drought Risk	0.032*	0.032	0.022	0.033	-0.074	-0.071	-0.032	-0.092**
	(0.018)	(0.018)	(0.018)	(0.019)	(0.067)	(0.068)	(0.042)	(0.038)
Wildfire Risk	-0.036	-0.041	-0.021	-0.031	-0.052	-0.067	-0.101*	-0.12*
	(0.071)	(0.074)	(0.078)	(0.074)	(0.074)	(0.076)	(0.055)	(0.056)
Near Coast	-0.033	-0.035*	-0.027	-0.032	0.061**	0.066**	0.052	0.056
	(0.019)	(0.019)	(0.019)	(0.020)	(0.027)	(0.027)	(0.032)	(0.032)
Beta	0.002	0.004	0.002	0.001	0.077**	0.077**	0.082**	0.079**
	(0.019)	(0.020)	(0.017)	(0.018)	(0.030)	(0.030)	(0.034)	(0.032)
SMB	0.036**	0.037**	0.034**	0.033**	0.013	0.014	0.015	0.020
	(0.014)	(0.013)	(0.014)	(0.014)	(0.019)	(0.019)	(0.015)	(0.012)
HML	-0.005	-0.008	-0.005	-0.001	-0.003	-0.007	-0.018	-0.019
	(0.025)	(0.025)	(0.025)	(0.026)	(0.024)	(0.023)	(0.021)	(0.019)
RMW	-0.012	-0.012	-0.013	-0.012	-0.010	-0.009	-0.004	-0.009
	(0.019)	(0.018)	(0.018)	(0.019)	(0.024)	(0.025)	(0.018)	(0.016)
CMA	-0.001	-0.003	-0.001	0.001	-0.032	-0.034	-0.046	-0.044
	(0.011)	(0.011)	(0.011)	(0.011)	(0.038)	(0.038)	(0.030)	(0.028)
GDP	5.78E-09	7.47E-09	3.87E-09	2.48E-09	-1.11E-06	-1.17E-06	1.29E-05	1.30E-05
	(2.06E-08)	(2.03E-08)	(2.04E-08)	(2.13E-08)	(1.15E-06)	(1.20E-06)	(2.17E-05)	(2.21E-05)
HHI	-0.019	-0.020	-0.027	-0.021	-0.104	-0.097	-0.045	-0.062
	(0.020)	(0.020)	(0.022)	(0.025)	(0.060)	(0.059)	(0.049)	(0.060)
M. Cap.	0.201***	0.198***	0.190***	0.191***	0.118**	0.124**	0.110***	0.111***
	(0.051)	(0.053)	(0.051)	(0.050)	(0.038)	(0.039)	(0.035)	(0.033)
FFO	-0.001	-0.001	-0.001	0.371E-04	0.001	0.001	-0.001	-3.08E-04
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	-0.030	-0.029	-0.032	-0.034	-0.106*	-0.105**	-0.096***	-0.108***
	(0.039)	(0.039)	(0.038)	(0.038)	(0.048)	(0.046)	(0.029)	(0.027)
Dividends	-1.30E-08	-9.02E-09	-4.59E-09	-7.31E-09	7.27E-08	7.06E-08	7.52E-08	1.02E-07
	(3.05E-08)	(3.16E-08)	(3.13E-08)	(3.12E-08)	(5.18E-08)	(5.43E-08)	(5.02E-08)	(4.68E-08)
ROA	-0.26**	-0.263***	-0.165	-0.199*	0.056	0.056	0.078	-0.001
	(0.084)	(0.082)	(0.092)	(0.097)	(0.372)	(0.362)	(0.359)	(0.356)
Volume	-1.66E-06	-9.04E-07	4.28E-07	-3.19E-06	3.15E-05	3.08E-05	3.38E-05	3.93E-05
	(5.69E-06)	(6.37E-06)	(6.37E-06)	(6.05E-06)	(1.28E-05)	(1.23E-05)	(1.29E-05)	(1.34E-05)
Constant	-0.076	-0.075	-0.077	-0.086	-0.150**	-0.150**	-0.015	-0.027
	(0.052)	(0.051)	(0.052)	(0.051)	(0.051)	(0.050)	(0.013)	(0.021)
Adj. R^2	0.638	0.640	0.628	0.631	0.643	0.640	0.622	0.621

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

To test this hypothesis, we split the sample at the median level of institutional ownership, distinguishing between REITs with relatively high institutional and high retail ownership. The Fama–MacBeth regressions, reported in Table 4.6, accounts for roughly 64% of the variance in outcomes, underscoring its strong explanatory performance. It reveals a clear divergence in risk sensitivity. The negative and significant relationship between hurricane risk and excess equity returns is driven entirely by REITs with higher institutional ownership. In contrast, REITs with greater retail ownership exhibit no statistically significant response to hurricane exposure. This suggests that institutional investors recognize and price hurricane risk more efficiently, while retail investors do not systematically incorporate it into their valuation decisions.

Effect of Physical Climate Risk Horizons

The estimated coefficients for hurricane risk remain relatively stable across the different projection horizons, ranging from –0.118 for current risk projections to –0.138 for the 30-year horizon. This consistency indicates that institutional investors systematically price greater exposure to hurricane risk in REIT excess returns. The slight increase in magnitude of the coefficients at longer horizons suggest that investors place greater emphasis on distant climate risk projections, reflecting a forward-looking component in pricing behavior. Overall, the results imply that physical climate risk is persistently and significantly priced into REIT equity excess returns, with only a modest intensification as the projection horizon extends.

4.7 Conclusion

Physical climate risks can have tangible effects on firms' financial performance, yet their pricing in capital markets remains only partially understood. The real estate sector is particularly exposed to such risks due to the inherent characteristics of real estate as an asset class, while Real Estate Investment Trusts (REITs) provide a transparent framework for analyzing their financial implications. To the best of our knowledge, this study provides the first comprehensive analysis of how forward-looking physical climate risks are priced across both real estate debt and equity markets, distinguishing between multiple hazard types and forecast horizons. Using a sample of U.S. REITs from 2021 to 2024, we link property-level exposures to flood, frost, hurricane, drought, and wildfire risks with capital market risk premia.

Our findings reveal that investors in REIT bond markets demand higher risk premia for exposure to flood, frost, drought and wildfire risks, suggesting that these physical hazards are perceived as material credit risk factors. In contrast, for the real estate equity market we observe that predominately hurricane risk is priced and negatively related with equity excess returns. Further analysis shows that ownership structure plays a crucial role in this finding, with institutional investors driving hurricane risk pricing. We assume that this is due to the fact that institutional investors have better access to analytical tools and can therefore make more informed investment decisions. Moreover, equity markets show limited differentiation across time horizons, with the pricing of longer-term physical climate risks being marginally more pronounced. Overall, our results highlight that physical climate risks are selectively priced, and that investor sophistication plays a central role in this process.

Navigating physical climate risk in capital markets remains challenging, as there is persistent uncertainty and complexity associated with climate models and data. A key reason for this uncertainty is the lack of standardized climate data and reporting. Due to limited data availability, we are only able to analyze a relatively small-time span, since current physical climate risk projections can only be applied retroactively for a few years (Ling et al., 2024). We address concerns related to the relatively short sample period by applying appropriate HAC corrections. In addition, although we control for a broad set of potential determinants of risk premia and returns, our results should not be interpreted as causal, but rather correlational relationships.

Consequently, several promising directions emerge for further research. One avenue lies in examining how the integration of physical climate risks into capital market pricing translates into opportunities for firms. For instance, REITs that are better protected against physical hazards may realize superior operating performance and long-term competitiveness also reflected in capital market performance. Another direction involves understanding the behavioral underpinnings of the observed divergence between institutional and retail investors in pricing hurricane risk. Either institutional investors may possess superior analytical capabilities, or retail investors might simply perceive such risks as immaterial to financial performance. Clarifying whether this pattern reflects informational inefficiency or rational inattention remains an important direction for future research but is beyond the scope of this study.

4.8 References

Addoum, J. M., Eichholtz, P., Steiner, E., & Yönder, E. (2024). Climate change and commercial real estate: Evidence from Hurricane Sandy. *Real Estate Economics, 52*(3), 687–713. https://doi.org/10.1111/1540-6229.12435

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008

Bolton, P., & Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance, 78*(6), 3677–3754. https://doi.org/10.1111/jofi.13272

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance, 76*(4), 1731–1772. https://doi.org/10.1111/jofi.13024

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics, 29*(2), 238–249. https://doi.org/10.1198/jbes.2010.07136

Carrão, H., Naumann, G., & Barbosa, P. (2018). Global projections of drought hazard in a warming climate: a prime for disaster risk management. *Climate Dynamics, 50*(5), 2137–2155. https://doi.org/10.1007/s00382-017-3740-8

Contat, J., Hopkins, C., Mejia, L., & Suandi, M. (2024). When climate meets real estate: A survey of the literature. *Real Estate Economics, 52*(3), 618–659. https://doi.org/10.1111/1540-6229.12489

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics, 80*(4), 549–560. https://www.jstor.org/stable/2646837

Duan, K., Sun, G., Caldwell, P. V., McNulty, S. G., & Zhang, Y. (2018). Implications of upstream flow availability for watershed surface water supply across the conterminous united states. *Journal of the American Water Resources Association, 54*(3), 694–707. https://doi.org/10.1111/1752-1688.12644

Faccini, R., Matin, R., & Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance, 155*, 106948. https://doi.org/10.1016/j.jbankfin.2023.106948

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy, 81*(3), 607–636. https://doi.org/10.1086/260061

Feng, Z., Lu-Andrews, R., & Wu, Z. (2024). Commercial real estate in the face of climate risk: insights from REITs. *Journal of Real Estate Research*, 1–29. https://doi.org/10.1080/08965803.2024.2352917

Ferson, W. E., & Harvey, C. R. (1999). Conditioning variables and the cross section of stock returns. *The Journal of Finance, 54*(4), 1325–1360. https://doi.org/10.1111/0022-1082.00148

Fisher, J. D., & Rutledge, S. R. (2021). The impact of Hurricanes on the value of commercial real estate. *Business Economics, 56*(3), 129–145. https://doi.org/10.1057/s11369-021-00212-9

Fuerst, F., & Warren-Myers, G. (2021). Pricing climate risk: Are flooding and sea level rise risk capitalised in Australian residential property? *Climate Risk Management, 34*, 100361. https://doi.org/10.1016/j.crm.2021.100361

Gilstrap, C., Petkevich, A., Sezer, O., & Teterin, P. (2022). REIT debt pricing and ownership structure. *The Journal of Real Estate Finance and Economics, 64*(4), 546–589. https://doi.org/10.1007/s11146-020-09806-0

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., & Schwert, M. (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies, 36*(11), 4588–4635. https://doi.org/10.1093/rfs/hhad041

Götz, L., Mager, F., & Zietz, J. (2024). The effect of wildfires on mortgage pricing: evidence from Portugal. *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-024-09982-3

Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let's get physical: Comparing metrics of physical climate risk. *Finance Research Letters, 46*, 102406. https://doi.org/10.1016/j.frl.2021.102406

Hartzell, J. C., Sun, L., & Titman, S. (2014). Institutional investors as monitors of corporate diversification decisions: Evidence from Real Estate Investment Trusts. *Journal of Corporate Finance, 25*, 61–72. https://doi.org/10.1016/j.jcorpfin.2013.10.006

Hoehn, B., Salzberger, H., & Bienert, S. (2024). Assessing climate risk quantification tools – mere fulfilment of duty or actually beneficial? *Journal of Property Investment & Finance, 43*(2), 142–167. https://doi.org/10.1108/JPIF-01-2024-0008

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics, 208*(1), 265–281. https://doi.org/10.1016/j.jeconom.2018.09.015

Hsu, P. H., Li, K., & Tsou, C. Y. (2023). The pollution premium. *The Journal of Finance, 78*(3), 1343–1392. https://doi.org/10.1111/jofi.13217

Huynh, T. D., Nguyen, T. H., & Truong, C. (2020). Climate risk: The price of drought. *Journal of Corporate Finance, 65*, 101750. https://doi.org/10.1016/j.jcorpfin.2020.101750

Issler, P., Stanton, R., Vergara-Alert, C., & Wallace, N. (2024). *Housing and mortgage markets with climate risk: Evidence from wildfires in California.* [Working paper]. Social Science Research Network. http://dx.doi.org/10.2139/ssrn.3511843

Kousky, C., Palim, M., & Pan, Y. (2020). Flood damage and mortgage credit risk: A case study of Hurricane Harvey. *Journal of Housing Research, 29*(sup1), S86–S120. https://doi.org/10.1080/10527001.2020.1840131

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies, 33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Ling, D. C., Robinson, S., Sanderford, A. R., & Wang, C. (2024). Climate change and commercial property markets. *Journal of Regional Science, 64*(4), 1066–1098. https://doi.org/10.1111/jors.12717

Liu, Y., & Wu, J. C. (2021). Reconstructing the yield curve. *Journal of Financial Economics, 142*(3), 1395–1425. https://doi.org/10.1016/j.jfineco.2021.05.059

Mastouri, A., Mendiratta, R., & Giese, G. (2022). Corporate bonds and climate change risk. *The Journal of Portfolio Management, 48*(10), 78–97. https://doi.org/10.3905/jpm.2022.1.421

McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics, 34*(4), 574–589. https://doi.org/10.1080/07350015.2015.1086655

Mueller, J., Loomis, J., & González-Cabán, A. (2009). Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. *The Journal of Real Estate Finance and Economics*, *38*(2), 155–172. https://doi.org/10.1007/s11146-007-9083-1

Murfin, J., & Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, *33*(3), 1217–1255. https://doi.org/10.1093/rfs/hhz134

NAREIT (2025). *REITs by the numbers.* https://www.reit.com/data-research/data/reits-numbers

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708. https://doi.org/10.2307/1913610

NOAA (2025). *National Centers for Environmental Information (NCEI) U.S. Billion dollar weather and climate disasters.* https://www.ncei.noaa.gov/access/billions

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics, 135*(2), 468–482. https://doi.org/10.1016/j.jfineco.2019.06.006

Pommeranz, C., & Steininger, B. I. (2020). Spatial spillovers in the pricing of flood risk: Insights from the housing market. *Journal of Housing Research*, *29*(sup1), S54–S85. https://doi.org/10.1080/10527001.2020.1839336

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 U.S. Elections. *The Review of Corporate Finance Studies*, *10*(4), 748–787. https://doi.org/10.1093/rcfs/cfab010

Ritchie, H., & Roser, M. (2024). *How are extreme weather events and the climate evolving in the United States?* Our World in Data. https://ourworldindata.org/us-weather-climate

Robinson, S., Sanderford, D., & Plass, L. (2022). *How to choose, use, and better understand climate-risk analytics.* https://knowledge.uli.org/reports/researchreports/2022/how-to-choose-use-and-better-understand-climate-risk-analytics

Sanders, B. F., Schubert, J. E., Kahl, D. T., Mach, K. J., Brady, D., AghaKouchak, A., Forman, F., Matthew, R. A., Ulibarri, N., & Davis, S. J. (2023). Large and inequitable flood risks in Los Angeles, California. *Nature Sustainability, 6*(1), 47–57. https://doi.org/10.1038/s41893-022-00977-7

Seltzer, L., Starks, L. T., & Zhu, Q. (2025). *Climate regulatory risks and corporate bonds.* [Working paper]. Social Science Research Network. http://dx.doi.org/10.2139/ssrn.3563271

Shenoy, S., Gorinevsky, D., Trenberth, K. E., & Chu, S. (2022). Trends of extreme US weather events in the changing climate. *Proceedings of the National Academy of Sciences, 119*(47). https://doi.org/10.1073/pnas.2207536119

Sirmans, C. S., Sirmans, G. S., Smersh, G. T., & Winkler, D. T. (2025). Perceptions of climate change and the pricing of disaster risk in commercial real estate. *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-025-10015-w

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics, 142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

Task Force on Climate-Related Financial Disclosures (2017). *Recommendations of the Task Force on Climate-Related Financial Disclosures.* https://www.fsb-tcfd.org/recommendations

Touma, D., Ashfaq, M., Nayak, M. A., Kao, S. C., & Diffenbaugh, N. S. (2015). A multi-model and multi-index evaluation of drought characteristics in the 21st century. *Journal of Hydrology, 526*, 196–207. https://doi.org/10.1016/j.jhydrol.2014.12.011

Wu, L., & Kim, S. K. (2024). Evaluating the economic and climate adaptation benefits of land conservation strategies in urban coastal regions of the U.S. and China. *Climate Risk Management, 45*, 100632. https://doi.org/10.1016/j.crm.2024.100632

Yi, D., & Choi, H. (2020). Housing market response to new flood risk information and the impact on poor tenant. *The Journal of Real Estate Finance and Economics, 61*(1), 55–79. https://doi.org/10.1007/s11146-019-09704-0

Zhang, L., & Leonard, T. (2019). Flood hazards impact on neighborhood house prices. *The Journal of Real Estate Finance and Economics, 58*(4), 656–674. https://doi.org/10.1007/s11146-018-9664-1

4.9 Appendix

Appendix 4.A – Description of Physical Climate Risk Data

Table 4.7: Description of Physical Climate Risk Data

	Description
General Information	Jupiter's Climate Score Global quantifies physical climate risk anywhere in the world. In our study we use the five perils described below for REIT properties in the United States. Peril metrics (e.g., wind speed, flood depth) are physical quantities from Global Climate Models (GCM)-driven modeling. Since different perils are expressed in heterogeneous units that are not directly comparable, these bands are subsequently mapped to generic risk tiers with qualitative labels: lowest, low, medium, high, and highest. This tier system provides a unit-agnostic, harmonized risk scale that facilitates comparison of exposure across different peril types.
Acute Risk: Flood	The flood peril metric used in this study is the projected flood depth for a 100-year return period. The flood model combines coastal flood, fluvial (river) flood, and pluvial (rainwater) floods; results are reported as a combined flood depth (maximum across types). Tiers/bands follow Sanders et al. (2023)
Acute Risk: Hurricane	The acute wind-speed metric used in this study represents the expected 1-minute sustained wind speed (km/h) for 100-year events, modeling tropical cyclones and large extratropical storms. Tiers/bands follow the Saffir–Simpson Hurricane Wind Scale classification.
Acute Risk: Wildfire	The wildfire metric estimates annual probability of a catastrophic wildfire affecting an asset, trained on high-resolution geospatial predictors. Baseline (1995) probabilities are scaled by changes in air temperature and humidity called vapor pressure deficit (VPD). Downscaling from ERA5 to 90 m incorporates additional geospatial features. Tiers/bands are based on quantiles across 430,000 global locations.
Chronic Risk: Frost	Cold peril metrics characterize extreme low-temperature exposure. Here, "cold days" are days per year with air temperature ≤ 0 °C / ≤ 32 °F. Tiers/bands are based on the distribution of cold days in populated regions globally.
Chronic Risk: Drought	Water stress is water demand divided by available water supply (WRI Aqueduct 4.0), delivered on the 90 m CSG grid. Demand projections reflect CMIP6 forcing and sectoral changes (domestic, industrial, livestock). Stress is computed over watershed boundaries (accounts for routing/flow accumulation). Tiers/bands are based on the distribution of water stress in populated regions and the work from Duan et al. (2018), Touma et al. (2015) and Carrão et al. (2018).
Climate Scenario	This study uses the SSP2 - RCP4.5 climate scenario. SSP2- RCP4.5, the "Middle of the road" or medium pathway extrapolates the past and current global development into the future. Emissions growth continues to increase then begins leveling out by 2050 and declining after. In the IPCC's 6th Assessment Report, this scenario was deemed to be the "most likely" scenario. This scenario is coupled with RCP 4.5 radiative forcing, resulting in likely global warming of 2.1–3.5 °C in 2100 compared to a 1986–2005 baseline average.
Time Horizons	2025 – 2100 in 5-year intervals.

Appendix 4.B – Aggregated and Normalize Physical Climate Risk Scores

We translate property-level hazard metrics into REIT-level exposures, computed separately for each peril (e.g., flood, frost, hurricane, drought, wildfire) and forecast horizon. We follow three steps: (i) aggregate raw scores across the REIT's quarter-t portfolio (equal-weighted), (ii) median-center within asset class, and (iii) min–max rescale within each hazard–time horizon cell and asset class to avoid negative values.

For each property i, hazard h and horizon k, the provider-supplied hazard metric is harmonized to a discrete 1–5 scale. Let $S_i^{(h,k)} \in \{1,2,3,4,5\}$ denote this harmonized raw peril score and let $\mathcal{A}_{jt}$ be the set of properties held by REIT j in quarter t. We first aggregate to the REIT level:

$$\mathrm{REITExp}_{\mathrm{jt}}^{(\mathrm{h,k})} = \frac{1}{|\mathcal{A}_{jt}|} \sum_{i \in \mathcal{A}_{jt}} S_i^{(h,k)}. \tag{4.B.1}$$

Next, let $c(j,t)$ denote the asset class of REIT j in quarter t (e.g., Industrial, Office, Residential). We median-center the REIT exposures cross-sectionally within asset class:

$$D_{(jt)}^{(h,k)} = REITExp_{(jt)}^{(h,k)} - Med\left(REITExp_{(\ell t)}^{(h,k)} : c(\ell,t) = c(j,t)\right). \tag{4.B.2}$$

Finally, we min–max normalize Equation 4.B.2 within the (h,k,t,c) cell to the unit interval:

$$\widetilde{\mathrm{REITExp}}_{jt}^{(h,k)} = \frac{D_{jt}^{(h,k)} - \underline{D}_{t,c}^{(h,k)}}{\overline{D}_{t,c}^{(h,k)} - \underline{D}_{t,c}^{(h,k)}} \in [0,1], \qquad \underline{D}_{t,c}^{(h,k)} = \min_{\mathrm{l}:\, c(\mathrm{l},t)=c} D_{\mathrm{l}t}^{(h,k)}, \ \ \overline{D}_{t,c}^{(h,k)} = \max_{\mathrm{l}:\, c(\mathrm{l},t)=c} D_{\mathrm{l}t}^{(h,k)}. \tag{4.B.3}$$

The former class median ($D = 0$) maps to

$$\lambda_{t,c}^{(h,k)} = \frac{-\underline{D}_{t,c}^{(h,k)}}{\overline{D}_{t,c}^{(h,k)} - \underline{D}_{t,c}^{(h,k)}} \in (0,1), \tag{4.B.4}$$

so that $\widetilde{\mathrm{REITExp}}_{jt}^{(h,k)} > \lambda_{t,c}^{(h,k)}$ indicates above-median exposure within class.

Time variation in $\widetilde{\mathrm{REITExp}}_{jt}^{(h,k)}$ reflects (i) portfolio changes that alter $\mathcal{A}_{jt}$ in Equation 4.B.1 and (ii) cross-sectional shifts within asset class that move the median and the min–max window used in Equations 4.B.2 – 4.B.3.

Appendix 4.C – Link to CAT Bond Risk Premium

The unconditional Fama-MacBeth regression averages of physical climate risk hazard premia may conceal time-varying dependence on catastrophe insurance market conditions. Since these market conditions, i.e. the cost and availability of catastrophe risk transfer, may vary over time, we test for state-dependent pricing by regressing the quarterly hazard price $\left(\widehat{\pi_t}(h)\right)$ on the catastrophe-insurance risk premium (CAT), a market-based proxy for (re)insurance stress. Let $\widehat{\pi_t}$ collect the quarter-t prices of risk from Equation (4.5). The time-series average price is:

$$\bar{\pi} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\pi_t}. \tag{4.C.1}$$

To study how hazard premia co-move with insurance-market stress, we regress the quarterly price of hazard h on the catastrophe-insurance spread:

$$\widehat{\pi_t}(h) = \alpha + \phi\,\mathrm{CAT_t} + e_t, \tag{4.C.2}$$

estimated by OLS with HAC standard errors. A positive ϕ indicates higher compensation for hazard h when CAT spreads widen.[20]

Table 4.8. Sensitivity of Hazard Prices to CAT Bond Insurance Risk Premia

Hazard	N	Share sig (%)	Median $\hat{\phi}$ (sig)	Sign (mode)
Flood Risk	14	79	+0.068	+
Drought Risk	14	43	-0.062	_
Frost Risk	14	29	-0,021	_
Hurricane Risk	14	0	_	n.s.
Wildfire Risk	14	0	_	n.s.

Notes: OLS of quarterly hazard price $\widehat{\pi_t}(h)$ on $\mathrm{CAT_t}$ with HAC SEs. Entries pool across seven horizons. ``Share sig'' is the fraction of hazard×time horizon cells with $p \leq 0.05$.

Table 4.8 shows that the quarterly price of flood risk co-moves positively with the catastrophe-insurance spread: in 79% of hazard–time horizon cells, the CAT slope is significant, and the median significant estimate is $\hat{\phi} \approx +0.068$. This points to conditional (state-dependent) pricing, rather than a stable, unconditional premium: in quarters when risk-transfer capacity is scarce, proxied by wider CAT bond insurance risk premia, investors demand a higher compensation for flood exposure; when capacity is limited, the flood premium compresses. By contrast, for hurricane risks, we do not find systematic co-movement with CAT bond insurance risk premia over the 2021 – 2024 window.

[20] We ensure the lack of structural breaks in the $\widehat{\pi_t}(h)$ time series using Quandt–Andrews sup-F diagnostics (with fixed trimming).

5 Conclusion

5.1 Executive Summary

This chapter provides a summary overview of the three individual research papers. It begins by outlining the research motivation and objectives, followed by a description of the data and methodology employed, and concludes with a summary of the key findings and their implications for both research and practice.

Paper 1: Does Real Estate Determine REIT Bond Risk Premia?

Research Motivation and Objectives

Real Estate Investment Trusts (REITs) regularly issue bonds in large volume to finance their business. Despite the economic significance of REIT bonds, academic research has predominantly focused on the risk and return characteristics of REIT stocks, leaving the public debt of REITs largely unexplored. However, a focused investigation of the risk drivers of REIT bonds is warranted because REITs are structurally different from regular corporations. Since REITs are legally required to invest at least 75% of their assets in real estate, derive 75% of their gross income from real estate-related activities, and distribute 90% of their taxable income to investors, their bonds are claims on the cash flows generated from operating commercial real estate. In contrast, bonds from regular corporations are serviced from cash flows derived from products or services. The different sources of cash flows lead to distinct risk and return profiles: real estate generates steady, often predictable rental income, while corporate earnings can be more volatile and subject to market competition and consumer preferences. Additionally, while most bond borrowing at the REIT level is unsecured, the tangible real estate assets of REITs are easier to value, and monitor compared to intangible assets like intellectual property, brand, or research and development efforts that other corporations possess. Due to these fundamental structural differences, this study analyzes REIT bonds in isolation.

The objective of this research paper is to understand whether and to what extent real estate factors, proxied by total real estate market return and REIT property type, predict REIT bond risk premia. In addition, it aims to understand if REIT property-type diversification is associated with lower bond risk premia.

Methodology and Data

Building on empirical asset pricing evidence that artificial neural networks outperform alternative methods in predicting returns and risk premia (Bianchi et al., 2021; Gu et al, 2020), this study employs a neural network model to analyze the determinants of REIT bond risk premia. Since the aim is not only to predict REIT bond yield spreads but shed light on the individual importance of determinants, it employs two model-agnostic methods for machine learning explainability: first-order feature importance and Accumulated Local Effects (ALE) plots. This study is based on a dataset comprising 33,857 REIT bond yield spreads from 2010 to 2022, along with 24 explanatory variables. These variables encompass data from the equity market, REIT equity data, bond market, REIT bond data, REIT accounting information, as well as total returns from the direct real estate market and REIT property-type, all aiming to explain REIT bond yield spreads.

Results and their Contribution to Science and Practice

The study presents evidence that there is a direct real estate factor in REIT bond yield spreads by showing that real estate market total return is an important and negatively related driver of REIT bond yield spreads. This is supported by the finding that REIT property type is an important determinant as well. Surprisingly, a property-type diversification risk premium is found. This means that investors generally do not reward property diversification on REIT level with a lower cost of debt. Consequently, this may suggest that investors prefer to property-diversify themselves by selecting a portfolio of specialized REITs. This study therefore complements findings from Anderson et al. (2015), Capozza and Seguin (1999) and Ro and Ziobrowski (2011), who study the effect of REIT-level property-type diversification on REIT performance and debt costs. Additionally, the importance of the REIT's market capitalization, the bond's coupon rate, and the bond's time to maturity hints at the presence of default risk premia, tax premia and liquidity risk premia, respectively, for REIT bonds, confirming prior research on corporate bonds (Campbell & Taksler, 2003; Chen et al., 2007; Goldberg & Nozawa, 2021; Longstaff et al., 2005). From a methodological standpoint, this study shows that a deep neural network outperforms an ordinary least squares regression (OLS) in predicting REIT bond risk premia out-of-sample. This improvement is driven less by nonlinearities and more by interaction effects in the data, as revealed by the ALE plots.

To the best of the authors knowledge this is the first study to predict REIT bond yield spreads and analyze its real estate drivers. Understanding the real estate-specific drivers that influence REIT bond risk premia is important for REITs, investors, and policymakers alike. For REITs, understanding the drivers of their yield spreads, i.e., their cost of public debt, is critical to timing new bond issues as favorably as possible and making strategic capital structure decisions. For investors, it facilitates risk management as rising yield spreads lead to a decline in bond values and vice versa. Policymakers can benefit by enacting informed regulations that promote a stable and robust market environment.

Paper 2: Location Matters: Local Real Estate Market Risk and Geographic Diversification in REIT Public Debt

Research Motivation and Objectives

Location is one of the most important value drivers for real estate. A growing body of literature examines the impact of geographic characteristics on the risk and return profiles of both private and public real estate equity investments (Fisher et al., 2022; Zhu & Lizieri, 2022). However, there is limited research on how location risks influence REIT debt. This is a notable gap, given that U.S. REITs rely heavily on bond financing to support their operations, with bond issuances remaining robust in recent years despite rising interest rates. In addition, bondholders may price risk differently than equity holders because they occupy a senior position in the capital structure, facing mainly downside risk, as their upside potential is limited to fixed coupon payments and principal repayment. This study aims to fill this gap by investigating how location-based risk, specifically local market volatility and geographic diversification, influence the pricing of REIT bonds.

Methodology and Data

This study uses a dataset of 30,186 monthly bond yield spreads from 2010 to 2023, along with 27 explanatory variables. We construct a local beta factor to measure an individual REIT's sensitivity to local real estate market risk. This beta reflects the sensitivity of each local real estate market’s total return in which a REIT holds assets to shocks in the aggregated national real estate market. Additionally, to capture geographic diversification of a REIT’s property portfolio, we calculate the Herfindahl-Hirschman Index (HHI). The control variables include REIT bond information, property location data, REIT-specific accounting measures, equity market data, and macroeconomic indicators. The empirical analysis combines machine learning (ML) and traditional econometric methods, leveraging the former's ability to capture complex, nonlinear patterns while retaining the interpretability offered by the latter, as demonstrated in prior studies (see, e.g., Krämer et al., 2023; Lorenz et al., 2023). Specifically, the study employs an artificial neural network (ANN) model to predict REIT bond yield spreads. The data patterns are then visualized using the eXplainable Artificial Intelligence (XAI) method, Accumulated Local Effects (ALE) plots. These visualizations guide the selection of model specifications for the final step, where a traditional ordinary least squares (OLS) regression with polynomial transformations is applied based on the inflections identified in the ALE plots, to provide clear measures of statistical significance.

Results and their Contribution to Science and Practice

The results show a local real estate market risk premium for REIT bonds. Investors demand higher compensation for holding bonds from REITs with property portfolios in locations that are more sensitive to real estate market shocks. This effect is consistently observed across all REITs, regardless of whether they operate in more volatile or more stable markets. Consistent with the author's hypothesis, the effect is less pronounced than the findings for REIT equities by Zhu and Lizieri (2022), likely due to the differing priority of claims, as bondholders have higher priority than equity holders and are therefore less sensitive to geographic risks.

Additionally, the results reveal a more nuanced, nonlinear relationship between geographic diversification and REIT bond risk premia than previously reported in the literature. For REITs with more concentrated portfolios, increasing geographic diversification leads to a decrease in bond risk premia, reflecting that the benefits of diversification, such as reduced cash flow volatility and lower exposure to local economic shocks, outweigh the potential increased costs associated with managing a dispersed property portfolio. However, for REITs that are already well-diversified, further diversification results in higher bond risk premia, suggesting that the costs of additional diversification exceed its benefits. The turning point occurs at a HHI value of 0.25, where a structural break in the data is identified that marks a shift in how investors price the risks of further diversification. This point can be seen as the optimal portfolio diversification for minimizing the cost of public debt from a REIT perspective. When interacting local beta and HHI, the study shows that for REITs operating in more volatile markets, the effect of geographic concentration on bond risk premia is amplified, resulting in a disproportionately larger increase in risk premia as concentration rises.

Understanding the link between fundamental location characteristics of commercial real estate and REIT bond risk premia provides valuable insights for REIT managers, investors, and bond portfolio managers. For REIT managers, these findings provide a framework for optimizing geographic market allocations over the long term through strategic adjustments in acquisition, development, and divestment decisions, with the aim of lowering the cost of future public debt issuances. For investors, the results show that local real estate market risk is a material driver of REIT bond risk premia in the secondary market, providing an additional lens for credit risk assessment beyond firm-level financial metrics. Bond portfolio managers can leverage these insights to refine pricing models and improve investment decisions.

Paper 3: Do Real Estate Capital Markets Care About Physical Climate Risk?

Research Motivation and Objectives

Advancing climate change is leading to more frequent and severe destructive weather events such as floods, storms, and droughts (see e.g., Ritchie and Roser, 2024; Shenoy et al., 2022). Institutional investors increasingly recognize climate change as a material financial risk (Krueger et al., 2020). Yet, despite this growing awareness, a majority of finance professionals and academics believe that climate-related risks remain insufficiently reflected in asset prices (Stroebel & Wurgler, 2021).

The real estate sector is particularly vulnerable to physical climate risk due to the immobility of its assets, their high capital intensity, and the long-term nature of property investments. While pricing impacts of physical climate risk have been shown at the asset level (see e.g., see e.g., Addoum et al., 2024; Contat et al., 2024; Fisher and Rutledge, 2021; Kousky et al., 2020; Sirmans et al., 2025), the pricing transmission of property level risk exposure into capital markets, specifically the cost of debt and equity, remains largely underexplored.

Real Estate Investment Trusts (REITs) offer a suitable empirical setting to analyze these transmission effects. As publicly traded portfolios of immobile, income-generating assets, their financial performance is highly sensitive to destructive weather events. In addition, REITs also exhibit greater asset-level transparency than non–real estate corporations. They typically disclose the location and characteristics of their property portfolios to investors, making physical climate risk assessment more feasible. In contrast, non–real estate corporations often do not reveal the geographic distribution and operational importance of physical assets (i.e., offices and production facilities) as part of their complex supply chains, making it difficult for investors to assess business disruption risk and its financial implications from local destructive weather events (Hain et al., 2022).

The objective of this study is to analyze the transmission of physical climate risk on the property level to the stock and bond markets by leveraging detailed asset-level physical climate risk data. In addition, given the distinct risk–return profiles of stocks and bonds, potential differences in the effects of physical climate risk on these securities are of particular interest to investigate. Furthermore, the analysis considers the role of REIT ownership structure in shaping climate risk pricing and examines whether pricing effects differ across short- and long-term climate risk horizons.

Methodology and Data

This study therefore uses two datasets: one covering the U.S. REIT equity market and the other the U.S. REIT public debt market. Both contain identical measures of forward-looking physical climate risk, covering flood, frost, hurricane, drought and wildfire risks, but differ in their dependent variables and in the set of control variables, reflecting the structural characteristics of each market. The analysis draws on forward-looking climate risk data from Jupiter Intelligence, a U.S.-based climate analytics provider. The dataset covers five peril types, i.e., flood, frost, hurricane, drought, and wildfire risk, at the level of individual REIT property coordinates. Information on property locations and holding periods is sourced from S&P Capital IQ Pro. The physical climate risk data is based on the Shared Socioeconomic Pathways (SSP) defined by the Intergovernmental Panel on Climate Change (IPCC). SSPs describe different climate change scenarios up to the year 2100 based on future social, economic, and technological trends. This study's physical climate risk data is based on the so called SSP2-4.5 pathway which is defined by the IPCC as the "middle of the road" scenario with medium future greenhouse gas emissions.

For the REIT bond market, a two-way fixed effects panel regression is estimated at the bond–quarter level. Each bond's physical climate exposure is aligned with the forecast horizon closest to its contractual maturity, ensuring that pricing reflects the bond's relevant risk horizon. For the REIT equity market, a Fama–MacBeth two-step regression is used to test whether physical climate risks are priced in equity excess returns. In the first step, rolling Fama–French five-factor models estimate REIT-level factor loadings. In the second step, quarterly cross-sectional regressions relate excess returns to physical climate risk exposures and lagged factor loadings. To assess heterogeneity in pricing behavior, the analysis is repeated separately for REITs with high vs. low institutional ownership.

Results and their Contribution to Science and Practice

Results show that physical climate risks are priced in real estate capital markets, but the nature of the pricing differs between debt and equity markets and investor types. Specifically, flood, frost, and wildfire risks are positively associated with higher REIT bond risk premia, indicating that credit investors demand higher risk premia to compensate for exposure to these hazards. These effects are statistically significant and economically meaningful, with risk premia increasing by up to nearly four percentage points for bonds issued by REITs with properties more exposed to high-risk areas. In contrast, in the REIT equity market, only hurricane risk is significantly priced, and it is negatively related to excess equity returns, suggesting that higher hurricane exposure is associated with lower REIT performance. This study further finds that this effect is driven by institutional investors, who might be better equipped to assess and incorporate such risks into their investment decisions. Finally, it is shown that the time horizon of physical climate risk expectation does not materially affect pricing, i.e. the pricing of longer-term physical climate risks is only marginally more pronounced.

This research paper makes several contributions to the literature on climate and real estate finance. First, it introduces a more robust and science-based measurement of physical climate risk by employing location-specific risk assessments rather than text-based proxies derived from news articles or corporate filings. In doing so, the findings challenge earlier studies that rely on textual measures of physical climate risk (see e.g., Faccini et al., 2023) and align more closely with research using forward-looking, asset-level risk assessments (see e.g., Ling et al., 2024). Second, the study adds greater nuance to the analysis of physical climate risks by distinguishing between multiple hazard types rather than relying on a single aggregated risk score or focusing on one hazard in isolation. Third, it provides a comprehensive perspective by jointly examining how physical climate risks are priced across real estate debt and equity capital markets, while also accounting for differences in time horizons and investor types.

5.2 Final Remarks

This dissertation examines how real estate–specific risks are transmitted into the pricing of public real estate capital markets. Such real estate-specific risks arise from the inherent heterogeneity and location dependency of real estate. While publicly listed REITs have transformed real estate into a more liquid and tradable financial asset, these fundamental characteristics of the underlying properties remain. The U.S. REIT market is the largest and most liquid globally, supported by a regulatory framework requiring high payout ratios, asset concentration in income-producing real estate, and transparency in financial reporting. These institutional features make REITs an ideal setting for analyzing the transmission of real estate fundamentals into capital-market pricing.

Across its three empirical studies, this dissertation demonstrates that capital markets do price real estate–specific risks, but the strength and form of this pricing depend on the type of risk and the characteristics of the market participants evaluating it. The first paper shows that a real estate factor is indeed present in REIT bond risk premia, complementing previous findings of such a real estate risk premium in the REIT equity market (Clayton & MacKinnon, 2003; Kroencke et al., 2018). Furthermore, the study shows that property-type diversification does not lead to lower debt costs. Instead, property-type diversified REITs may face higher spreads, likely reflecting increased complexity in management and outside valuation. This challenges the conventional notion that diversification is always beneficial from a financing perspective but confirms prior studies on the increasing effects of diversification on bank loan costs (Capozza & Seguin, 1999) for public debt markets.

The second paper extends the analysis to explicitly location-based risk, providing evidence that exposure to local market volatility, measured via a local beta factor, is positively priced in REIT bond spreads. This aligns with the notion of structural models of credit risk, such as Merton (1974), where increased asset volatility elevates the default risk perceived and priced by debt investors. As expected, the effect is less pronounced for REIT bonds compared to REIT equity as shown by Zhu and Lizieri (2022) which can be explained by the different in risk-return profiles and claim order in the capital structure between bondholders and shareholders. Moreover, the study identifies a nonlinear effect of geographic diversification, where moderate diversification reduces risk premia but both excessive diversification and low diversification leads to higher costs of debt. We identify an optimal degree of geographic diversification at an HHI value of approximately 0.25, beyond which both further concentration and further diversification become less beneficial from a REIT's perspective. This finding underscores that capital markets distinguish between economically meaningful diversification and overcomplexity, and that a REIT's spatial strategy must therefore be actively optimized. In addition, a positive and reinforcing interaction effect is found between higher geographic concentration and more volatile markets leading to disproportionately larger increase in bond risk premia.

The third paper demonstrates that bond markets and to a lesser extent equity markets incorporate expectations of future climate hazard exposure into pricing. Further analysis shows that ownership structure plays a crucial role in this finding, with institutional investors driving the risk pricing in the equity markets. We assume that this is due to the fact that institutional investors have better access to analytical tools and can therefore make more informed investment decisions. Moreover, equity markets show limited differentiation across time horizons, with the pricing of longer-term physical climate risks being marginally more pronounced. Importantly, this evidence is based not on realized disasters but on forward-looking, asset-level risk projections, indicating that public real estate capital markets are beginning to price physical climate risk proactively rather than solely in response to historical events.

Methodologically, the dissertation shows that machine learning models, particularly artificial neural networks, supported by explainable AI techniques, are powerful tools for predicting capital-market pricing. This adds to the growing evidence on superior predictive performance of machine learning in asset pricing due to detection of complex nonlinearities and interaction effects (Bianchi et al., 2021; Gu et al., 2020; Kelly et al., 2024; Leippold et al., 2022; Leow & Lindenthal, 2025). However, traditional econometric methods remain indispensable for statistical interpretability and formal inference.

As with any empirical study, certain limitations need to be acknowledged. First, the analysis of public debt markets begins in 2010 due to the limited availability and reliability of REIT bond data prior to that year. As a result, major historical episodes such as the dot-com bubble and the Global Financial Crisis (GFC) are not captured, preventing definitive conclusions about the drivers of bond risk premia over longer economic cycles. Moreover, the TRACE bond data is self-reported by market participants and, despite extensive cleaning procedures, may still contain residual reporting errors. Second, the findings are based exclusively on the U.S. capital market. While this capital market is the largest globally, the results may not fully generalize to other settings, such as European or Asian public real estate markets.

This dissertation improves the understanding of the integration between real estate and capital markets, thereby supporting more efficient capital allocation and greater capital market stability. The findings carry implications for multiple stakeholders. For REIT managers the implications are twofold. First, understanding how bond and equity markets respond to specific real estate-specific risks is critical for capital structure decisions, i.e. when to issue or withdraw equity or debt capital. Second, knowledge about the effects of geographic risks and diversification decisions on capital market pricing has important implications for portfolio strategy. For investors, the results provide empirical grounding for risk pricing models and asset allocation frameworks that explicitly incorporate location- and hazard-based fundamentals. For policymakers and regulators, the dissertation provides evidence that capital markets recognize physical climate risk, but not yet uniformly or comprehensively, suggesting a role for improved disclosure frameworks and standardization.

5.3 References

Addoum, J. M., Eichholtz, P., Steiner, E., & Yönder, E. (2024). Climate change and commercial real estate: Evidence from Hurricane Sandy. *Real Estate Economics, 52*(3), 687–713. https://doi.org/10.1111/1540-6229.12435

Anderson, R. I., Benefield, J. D., & Hurst, M. E. (2015). Property-type diversification and REIT performance: An analysis of operating performance and abnormal returns. *Journal of Economics and Finance, 39*(1), 48–74. https://doi.org/10.1007/s12197-012-9232-0

Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond risk premiums with machine learning. *The Review of Financial Studies, 34(2), 1046–1089* https://doi.org/10.1093/rfs/hhaa062

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance, 58*(6), 2321–2350. https://doi.org/10.1046/j.1540-6261.2003.00607.x

Capozza, D. R., & Seguin, P. J. (1999). Focus, transparency and value: The REIT evidence. *Real Estate Economics, 27*(4), 587–619. https://doi.org/10.1111/1540-6229.00785

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *The Journal of Finance, 62*(1), 119–149. https://doi.org/10.1111/j.1540-6261.2007.01203.x

Clayton, J., & MacKinnon, G. (2003). The relative importance of stock, bond and real estate factors in explaining REIT returns. *The Journal of Real Estate Finance and Economics, 27*(1), 39–60. https://doi.org/10.1023/A:1023607412927

Contat, J., Hopkins, C., Mejia, L., & Suandi, M. (2024). When climate meets real estate: A survey of the literature. *Real Estate Economics, 52*(3), 618–659. https://doi.org/10.1111/1540-6229.12489

Faccini, R., Matin, R., & Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance,* 155, 106948. https://doi.org/10.1016/j.jbankfin.2023.106948

Fisher, G., Steiner, E., Titman, S., & Viswanathan, A. (2022). Location density, systematic risk, and cap rates: Evidence from REITs. *Real Estate Economics*, *50*(2), 366–400. https://doi.org/10.1111/1540-6229.12367

Fisher, J. D., & Rutledge, S. R. (2021). The impact of Hurricanes on the value of commercial real estate. *Business Economics, 56*(3), 129–145. https://doi.org/10.1057/s11369-021-00212-9

Goldberg, J., & Nozawa, Y. (2021). Liquidity supply in the corporate bond market. *The Journal of Finance, 76*(2), 755–796. https://doi.org/10.1111/jofi.12991

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let's get physical: Comparing metrics of physical climate risk. *Finance Research Letters,* 46, 102406. https://doi.org/10.1016/j.frl.2021.102406

Kelly, B., Malamud, S., & Zhou, K. (2024). The Virtue of Complexity in Return Prediction. *The Journal of Finance 79*(1), 459–503. https://doi.org/10.1111/jofi.13298

Kousky, C., Palim, M., & Pan, Y. (2020). Flood damage and mortgage credit risk: A case study of Hurricane Harvey. *Journal of Housing Research, 29*(sup1), S86–S120. https://doi.org/10.1080/10527001.2020.1840131

Krämer, B., Nagl, C., Stang, M., & Schäfers, W. (2023). Explainable AI in a real estate context – Exploring the determinants of residential real estate values. *Journal of Housing Research, 32*(2), 204–245. https://doi.org/10.1080/10527001.2023.2170769

Kroencke, T. A., Schindler, F., & Steininger, B. I. (2018). The anatomy of public and private real estate return premia. *The Journal of Real Estate Finance and Economics, 56*(3), 500–523. https://doi.org/10.1007/s11146-017-9646-8

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies, 33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Leippold, M., Wang, Q., & Zhou, W. (2022). Machine learning in the Chinese stock market. *Journal of Financial Economics, 145*(2), 64–82. https://doi.org/10.1016/j.jfineco.2021.08.017

Leow, K., & Lindenthal, T. (2025). Enhancing real estate investment trust return forecasts using machine learning. *Real Estate Economics*, 53, 574–606. https://doi.org/10.1111/1540-6229.12527

Ling, D. C., Robinson, S., Sanderford, A. R., & Wang, C. (2024). Climate change and commercial property markets. *Journal of Regional Science, 64*(4), 1066–1098. https://doi.org/10.1111/jors.12717

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The Journal of Finance, 60*(5), 2213–2253. https://doi.org/10.1111/j.1540-6261.2005.00797.x

Lorenz, F., Willwersch, J., Cajias, M., & Fuerst, F. (2023). Interpretable machine learning for real estate market analysis. *Real Estate Economics, 51*(5), 1178–1208. https://doi.org/10.1111/1540-6229.12397

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470. https://doi.org/10.2307/2978814

Ritchie, H., & Roser, M. (2024). *How are extreme weather events and the climate evolving in the United States?* Our World in Data*.* https://ourworldindata.org/us-weather-climate

Ro, S., & Ziobrowski, A. J. (2011). Does focus really matter? Specialized vs. diversified REITs. *The Journal of Real Estate Finance and Economics, 42*(1), 68–83. https://doi.org/10.1007/s11146-009-9189-8

Shenoy, S., Gorinevsky, D., Trenberth, K. E., & Chu, S. (2022). Trends of extreme US weather events in the changing climate. *Proceedings of the National Academy of Sciences, 119*(47). https://doi.org/10.1073/pnas.2207536119

Sirmans, C. S., Sirmans, G. S., Smersh, G. T., & Winkler, D. T. (2025). Perceptions of climate change and the pricing of disaster risk in commercial real estate. *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-025-10015-w

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance*? Journal of Financial Economics, 142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

Zhu, B., & Lizieri, C. (2022). Local beta: Has local real estate market risk been priced in REIT returns? *The Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-022-09890-4

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