Climate Risks in Real Estate: Implications for Investment and Financing Strategies

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Declaration on the Use of Artificial Intelligence (AI)

I would like to acknowledge the use of AI-based systems as trivial tools limited to spelling and grammar checking in this thesis. All intellectual content, analyses, and conclusions are solely the work of the authors. As of the time of writing, no official or specific guidelines of the University of Regensburg or the Faculty of Business Administration, Economics, and Information Systems regarding the use of AI in dissertations have been adopted. Therefore, reference is made to the guidelines of the Faculty of Physics of the University of Regensburg, dated January 24, 2024.

Contents

List of Abbreviations

AIF	alternative investment fund
API	application programming interface
AUHI	atmospheric urban heat island
BERDO	Building Emissions Reduction and Disclosure Ordinance
BVI	Bundesverband Investment und Asset Management
CAGR	compound annual growth rate
CapEx	capital expenditure
CBD	central business district
CRE	commercial real estate
CSRD	Corporate Sustainability Reporting Directive
D/E	debt-to-equity
DSCR	debt service coverage ratio
EPA	U.S. Environmental Protection Agency
ESG	environmental, social, and governance
FFO	funds from operations
FM	Fama-MacBeth
GAM	generalized additive model
GAR	green asset ratio
GDP	gross domestic product
GfK	Growth from Knowledge
GHG	greenhouse gas
GIS	geographic information system
GLS	generalized least squares
GVIF	generalized variance inflation factor
HDD	heating degree day
HHI	Herfindahl–Hirschman Index
HVAC	heating, ventilation und air conditioning
IPO	initial public offering
IQR	interquartile range

IRA	Inflation Reduction Act
IRR	internal rate of return
IRS	Internal Revenue Service
ISSB	International Sustainability Standards Board
ITC	investment tax credit
KPI	key performance indicator
LM	Lagrange multiplier
LL97	Local Law 97
LTV	loan-to-value
MAE	mean absolute error
MAPE	mean absolute percentage error
M/B	market-to-book
MdAPE	median absolute percentage error
MSA	metropolitan statistical area
MWh	megawatt-hour
NAREIT	National Association of Real Estate Investment Trusts
NGFS	Network for Greening the Financial System
NI	net income
NOI	net operating income
NZBA	Net Zero Banking Alliance
OLS	ordinary least squares
OpEx	operating expenses
PAI	principal adverse impact
P/B	price-to-book
P/NAV	price-to-net asset value
PBR	principles-based requirements
PCAF	Partnership for Carbon Accounting Financials
POIs	points of interest
PPA	power purchase agreement
PV	photovoltaic
REC	renewable energy certificate
REIT	real estate investment trust
RMSE	root mean squared error
ROA	return on assets
ROI	return on investment

ROE	return on equity
RRSE	relative root squared error
RTS	Regulatory Technical Standards
SEC	U.S. Securities and Exchange Commission
SDG	Sustainable Development Goal
SFDR	Sustainable Finance Disclosure Regulation
SUHI	surface urban heat island
TCFD	Task Force on Climate-related Financial Disclosures
UHI	urban heat island
VIF	variance inflation factor
YoY	year-on-year

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1 Introduction

The publication of the *Stern Review* (Stern, 2007) marked a critical moment in the climate change debate, drawing global attention to its profound and far-reaching economic consequences. Since then, the growing visibility of climate-related risks has underscored their critical importance to financial stability. At the current pace of climate change, global financial assets could face climate-related write-downs of up to US$2.5 trillion (Dietz et al., 2016). Increasingly, climate-induced default risks are prompting investors to reallocate capital toward lower-risk asset classes—a shift that may depress asset prices and threaten financial stability (Dafermos et al., 2018).

While less climate-resilient industries may initially manage risks through financial integration with broader markets, they are likely to experience sustained capital outflows and shrinking investment opportunities over time (Albert et al., 2021). In turn, this worsens the capital shortfall needed to finance the transition to a low-carbon economy. As a result, the repricing of climate-exposed asset classes is expected to intensify, amplifying the long-term economic costs of climate change. According to Carney (2015), this reassessment of asset values stems from three main channels: *physical risks*, *transition risks*, and *liability risks*.

Among all asset classes, real estate is not only the largest (Moss & Farrelly, 2024)[1] but also the most vulnerable due to its inherent characteristics and exposure to climate-related risks. First, as a physical, bricks-and-mortar asset class, real estate is directly impacted by *physical risks*—both acute (such as floods or hurricanes) and chronic (for example, rising temperatures or sea levels) (Contat et al., 2024). Second, with the global real estate sector accounting for over one-third of global energy use and emissions (IEA, 2023), it faces growing transition risks driven by technological and regulatory shifts towards a low-carbon economy. As investor sentiment evolves, markets are adjusting: high-carbon assets are losing value, while lower-carbon alternatives are gaining (Bolton & Kacperczyk, 2023). Third, both physical and transition risks translate into *liability risks*

[1]While most of this consists of residential real estate, much of it owner-occupied and not traditionally considered an asset class, it still plays a critical role in global financial market stability, primarily through the insurance and mortgage sectors.

for market participants. These may stem from litigation over regulatory non-compliance (for example, emissions standards or disclosure failures) or financial claims related to climate-related property damage. Beyond direct liabilities for property owners, asset values are further affected by financed emissions and related risk considerations on the debt side (Elderson, 2023). For lenders, rising liability risks—often outside their control—can lead to underinvestment (Boyer & Laffont, 1997) and higher risk premiums, both of which carry significant implications for real estate markets.

Given the significance of these risks for the real estate asset class—and by extension, for financial stability—this thesis explores their implications for property investment and financing strategies in greater depth. A deeper understanding of these risks is crucial for accurately assessing potential repricing effects across sectors and for informing the decisions of policymakers and financial regulators. It is also essential for ensuring the efficient reallocation of capital needed to support the decarbonization of the built environment.

Significantly, identifying and quantifying risk drivers goes beyond measuring economic costs or financial losses. It enables market participants to anticipate regulatory developments and unlock new sources of value and revenue. This insight becomes even more relevant in the current context of geopolitical uncertainty and economic strain, where real estate investors often prioritize short-term profit over long-term value creation (Chacon et al., 2024).

The remainder of this dissertation is organized into four articles, each addressing one or more of the three principal risk channels affecting real estate markets. Together, these articles take a comprehensive view, spanning both equity and debt markets, listed and unlisted sectors and direct as well as indirect property investments. **Article One** investigates how spatial urban heat island (UHI) effects influence residential real estate prices, showing how physical climate risks contribute to the total costs of climate change beyond direct material damage. **Article Two** examines the impact of rooftop solar potential on the financial performance of real estate investment trusts (REITs), highlighting both an additional revenue source and a tool for managing transition risks. **Article Three** analyzes how disclosure practices, framed by the Sustainable Finance Disclosure Regulation (SFDR), affect the returns of non-listed real estate vehicles. It also assesses how the regulation's structure and objectives function within the real estate sector. **Article Four** quantifies how banks factor transition and liability risks into loan pricing and explores how lenders are scaling their investments to mobilize the capital required for the sector's decarbonization. The dissertation concludes with a summary of key findings and their implications for industry, policy, and academia.

1.1 Research Questions

To address the research question of how climate-related risk factors may affect the real estate asset class, four articles examine the transmission channels of *physical*, *transition*, and *liability risks* in more detail. This section provides an overview of these articles, summarizing their research questions, data sources, and methodological approaches.

Quantifying the Impact of Urban Heat Islands on Residential Property Prices

- How do UHI effects influence residential property prices?
- Do physical climate risks go beyond direct building damage and also impact the amenity value of climate?
- What are the implications for the location choices of households?

Leveraging a spatially high-resolution temperature dataset of more than 10 billion observations provided by Meteoblue, covering the entire city of Berlin on a 30x30 meters grid, this study examines how UHIs affect residential property prices between 2014 and 2023. For property data, information from over 100 listing platforms across Germany is aggregated, incorporating prices as well as relevant hedonic characteristics. The analysis employs both a linear regression model and a generalized additive model (GAM).

Rooftop Solar Potential and Financial Performance of REITs

- How does the potential for rooftop solar adoption impact the financial performance of REITs?
- Does the carbon intensity of local electricity grids to which REIT properties are connected play a significant role in this relationship?
- Beyond mitigating transition risks, does the potential for on-site renewable energy generation offer additional revenue streams?

Using Google's Solar API, we collect data on rooftop areas and the associated potential for solar panel installation for approximately 90,000 U.S. REIT properties. Additionally, we assess the carbon intensity of the respective electric grids to which these properties are connected. By integrating this data with firm characteristics and financial information from S&P Capital IQ Pro and Refinitiv Datastream, we analyze the effects on stock performance, operating performance, and firm values over the period from 2012 to 2023. The analysis relies on a fixed effects model and a Fama and MacBeth (1973) regression.

Unveiling the Impact of SFDR on Unlisted Real Estate Funds: A J-Curve and Panel Regression Analysis

- How do the SFDR categories affect the internal rate of return (IRR) of non-listed real estate funds?
- What implications does this have for the initial returns of the funds, considering that private equity returns typically follow a J-curve pattern?
- How does the SFDR currently function in the context of non-listed real estate vehicles, and does it fulfill its intended purpose?

This article relies on a dataset of monthly IRR observations from 54 non-listed real estate funds managed by one of the largest European service capital investment firms from 2021 to 2023. Given the relatively limited number of funds launched around the time of the SFDR's introduction, the dataset represents a well-balanced and representative sample. Using cubic spline interpolation and a random effects model, the study quantifies differences in returns both during the initial investment period and across the entire observation period.

Is there a Green Discount in Commercial Real Estate Lending?

- Do commercial real estate lenders account for climate-related transition and liability risks in their loan terms?
- Therefore, are there differences in loan spreads and loan-to-value (LTV) ratios between green and non-green properties which indicate a potential green discount?
- Have banks been able to increase their green asset ratio (GAR) over time and provide more debt capital to support the decarbonization of the real estate sector?

This article draws on a unique loan-level dataset covering more than 700 European investment properties, with a total loan volume of more than €30 billion from 2018 to 2023. Interest rates are explicitly adjusted for the base rate and all maturity-related spreads, which allows for the isolation of systematic and unsystematic risk components, such as climate change risks. A hedonic regression following Rosen (1974) is applied to quantify a potential green discount in loan terms.

1.2 Co-Authors, Submissions, and Conference Presentations

The following provides an overview of individual co-authors, submissions, and conference presentations.

Paper 1

Quantifying the Impact of Urban Heat Islands on Residential Property Prices

Authors: Anna Knoppik, Marcelo Cajias, Felix Weinel, Sebastian Leutner, Wolfgang Schäfers

Publication Details: Submission to *Real Estate Economics*.

Conference Presentation: Presented at the 31st European Real Estate Society Annual Conference 2025 in Athens, Greece

Paper 2

Rooftop Solar Potential and Financial Performance of REITs

Authors: Sebastian Leutner, Benedikt Gloria, Ben Höhn, Sven Bienert

Publication Details: Following peer review, revised manuscript resubmitted (22nd of August 2025) to the *Journal of Sustainable Finance & Investment*

Conference Presentation: Presented at the 30th European Real Estate Society Annual Conference 2024 in Sopot & Gdańsk, Poland and the 41st American Real Estate Society Annual Conference 2025 in Tucson, United States

Award: Received the 2024 European Real Estate Society Best PhD Paper Award

Paper 3

Unveiling the Impact of SFDR on Unlisted Real Estate Funds: A J-Curve and Panel Regression Analysis

Authors: Benedikt Gloria, Sebastian Leutner, Sven Bienert

Publication Details: Accepted (14th of March 2024) and published (4th of March 2025) in the *Journal of Property Investment & Finance*

Conference Presentation: Presented at the 29th European Real Estate Society Annual Conference 2023 in London, United Kingdom

Paper 4

Is there a Green Discount in Commercial Real Estate Lending?

Authors: Sebastian Leutner, Benedikt Gloria, Sven Bienert

Publication Details: Accepted (3rd of January 2024) and published (20th of August 2024) in the *Journal of Property Investment & Finance*

Conference Presentation: Presented at the 23rd African Real Estate Society Annual Conference 2024 in Livingstone, Zambia

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2 Quantifying the Impact of Urban Heat Islands on Residential Property Prices

2.1 Abstract

Frequent and persistent heat effects in urban environments, particularly urban heat islands (UHIs), pose an increasing risk to cities. However, their economic impact on housing markets remains underexplored. This study employs a semi-parametric approach to examine the relationship between UHI intensity and residential property prices, drawing on a unique building-level dataset with temperature measurements taken twice daily at 1 p.m. and 4 a.m. We find a strong, persistent negative relationship, with nighttime temperatures showing the most pronounced and lasting effect. Spatial analysis reveals significant variation, with differing patterns of heat exposure and resilience between central and peripheral areas. Socioeconomic disparities worsen the issue. Lower-income neighborhoods experience higher UHI exposure, underscoring climate-related spatial inequalities. Our results suggest that property prices reflect thermal risks and neighborhood microclimates. This study provides the first building-level evidence of the economic impact of UHIs, offering critical insights for investors, policymakers and urban planners aiming to strengthen heat resilience and promote equitable mitigation in housing markets.

Keywords: *Urban heat island; residential property prices; housing market; physical climate risk; temperature*

2.2 Introduction

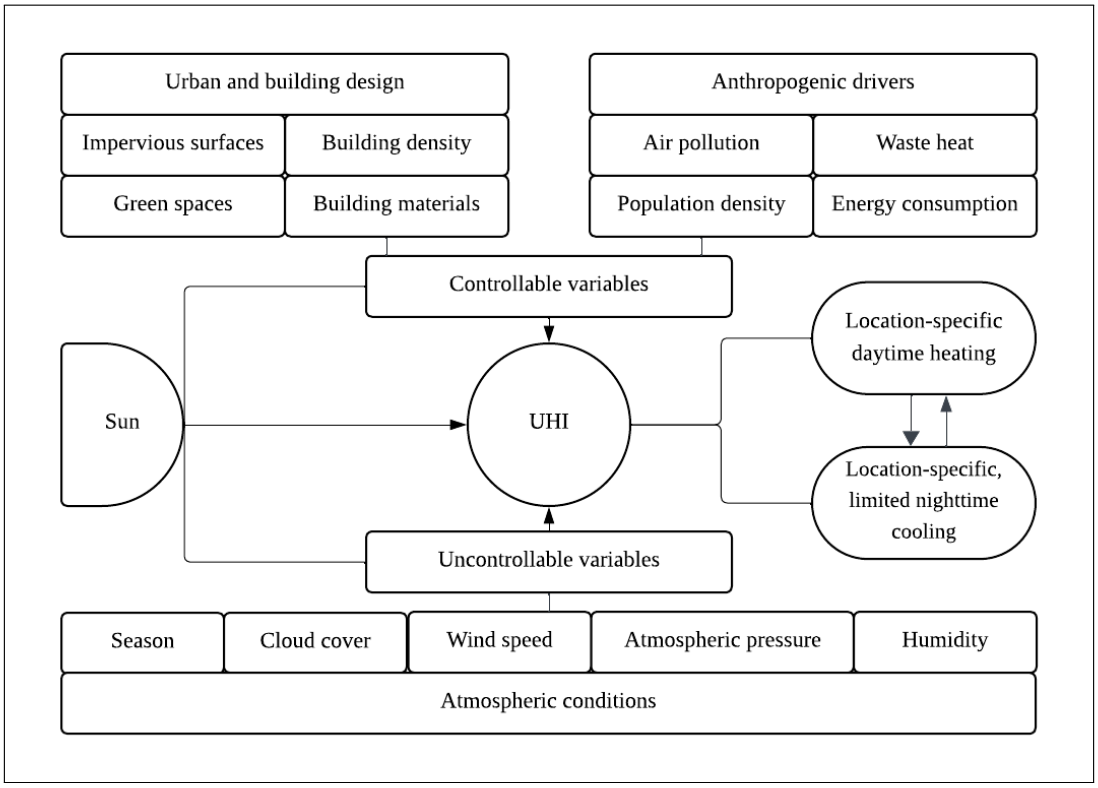
Research indicates that climate-related risks have a significant impact on global real estate markets.[1] Among these, increasingly frequent and intense heat extremes in urban environments pose a particular threat to the built environment and its inhabitants (IPCC, 2023). In fact, heat-related hazards often account for the majority of fatalities from natural disasters (Gabriel & Endlicher, 2011). By 2100, an estimated 75% of the global population could be at heightened risk of heat-related excess mortality, according to estimates based largely on evidence from mid-latitude cities in North America and Europe (Mora et al., 2017). This danger is further intensified by the UHI effect (Heaviside et al., 2016).

The UHI effect describes the phenomenon where urban temperatures are significantly higher than those in surrounding suburban or rural areas (Oke, 1982). However, UHI intensity also varies within cities due to factors such as building density, building materials and urban design, resulting in temperature differences between neighborhoods and even individual buildings. Areas with high-density development, extensive impervious surfaces and heat-absorbing building materials are especially vulnerable. Interactions with other environmental factors, such as air pollution, can further amplify UHI effects (H. Li et al., 2018). Urban areas, therefore, cause and suffer the most from UHIs. While UHIs typically result in average temperature increases of 4 to 6 degrees Celcius (°C) (7.2 to 10.8 degrees Fahrenheit (°F)) higher compared to rural areas, localized hotspots can reach up to 10°C (18°F) above the rural baseline (Iodice et al., 2024). The complex drivers of UHIs, ranging from controllable urban factors to uncontrollable environmental conditions, are illustrated in Figure 2.1.

A critical aspect of UHI exposure is its unequal distribution across socioeconomic groups. Higher-income households are more likely to live in cooler neighborhoods with favorable microclimates, reflecting their greater financial flexibility and willingness to pay for climate-related amenities (Borsky et al., 2024). In contrast, lower-income residents are often concentrated in hotter areas characterized by high building density, limited green infrastructure and reduced adaptive capacity. This climate-driven residential sorting deepens existing socioeconomic inequalities and further reduces the appeal and demand of already disadvantaged urban neighborhoods. As with other climate-related risks, the most vulnerable populations bear the greatest burden (Contat et al., 2024).

[1] See Contat et al. (2024) for a comprehensive overview of climate-related risks and definitions.

Figure 2.1: Drivers of UHI



The figure shows how anthropogenic and environmental factors interact to shape UHI effects. Controllable variables, such as urban form, building design and anthropogenic drivers, directly influence UHI, while uncontrollable variables, such as atmospheric conditions and solar radiation, do not. The diagram also differentiates between daytime UHI (heat exposure) and nighttime UHI (limited cooling potential). Source: Author's illustration based on Rizwan et al. (2008).

Beyond its human, social and spatial implications, excessive heat also undermines the functionality of buildings and urban infrastructure, imposing significant financial costs on owners and users. Across all building types, changing climatic conditions degrade thermal performance, increase the risk of overheating and raise cooling demand (Dodoo & Gustavsson, 2016). Rising energy consumption, already a major primary cost driver, is further compounded by pronounced peaks in electricity demand, which can disproportionally inflate operating expenses (Dirks et al., 2015). These peak load requirements also influence the selection and sizing of heating, ventilation und air conditioning (HVAC) systems. Consequently, UHIs raise ongoing operational costs and also drive capital expenditures for building design and system upgrades necessary to maintain indoor thermal comfort.

While UHI price effects are harder to quantify than direct property damage from acute climate risks such as floods, hurricanes and wildfires, the loss of climate-related amenities represents a significant share of total climate-related damages (Sinha & Cropper, 2013). Risks associated with UHIs, such as deteriorating air quality, overburdened electricity and water infrastructure, and poor indoor climate conditions, can significantly affect housing prices at both the neighborhood and individual property levels.

Despite the far-ranging effects of UHIs, their economic impact on real estate markets remains underexplored. As Contat et al. (2024) emphasize, research on chronic climate risks like UHIs is increasingly important given projected rises in extreme temperatures. The authors highlight an urgent need for more granular data and analysis to understand how real estate markets respond to rising temperatures and shifting spatial patterns. Most existing studies focus on national or state-level temperature effects, while city-level research remains limited. Where available, studies often rely on cross-city comparisons or coarse spatial data, making it difficult to assess UHI-related economic impacts at the neighborhood or individual property level.

This study addresses this critical research gap by estimating the effect of temperature deviations on local residential property prices using a GAM. To our knowledge, this is the first paper to apply granular, building-level temperature data to assess the economic impacts of UHIs within a single city. We incorporate temperatures at two times of day: 4 a.m. to capture overnight cooling potential and 1 p.m. to reflect daytime heat exposure. This allows us to analyze spatial heterogeneity based on proximity to the central business district (CBD) and urban green spaces, as well as temporal dynamics by tracking how UHI intensity evolves and influences return and risk parameters. We also account for socioeconomic conditions that shape neighborhood-level sensitivity to heat. This multidimensional approach offers a comprehensive understanding of how localized UHI effects influence urban housing markets.

Our results show that UHI intensity, measured twice daily at 4 a.m. and 1 p.m., has a negative effect on residential property prices. While the magnitude of the effect differs between daytime and nighttime measurements, the general pattern remains consistent. Cooler-than-average locations tend to command price premiums, whereas above-average UHI exposure results in price discounts. The effects vary spatially, influenced by urban structure and amenities. Differences in heat resilience and exposure reveal varying market sensitivities between central and peripheral locations. Proximity to green spaces is a critical factor, shaping how thermal stress is reflected in property values. Similarly, household income correlates with differing sensitivity to UHI, underscoring socio-economic disparities in climate adaptation. Nighttime UHI intensity has the strongest and most persistent impact on long-term price appreciation and risk-adjusted returns, confirming the importance of overnight cooling in urban climate resilience. Overall, our findings suggest that the market prices UHI exposure as a property-specific climate risk, reflecting both its spatial variation and financial relevance.

The remainder of the paper is structured as follows: The next section reviews the relevant literature and situates our research within it. This is followed by a description of the data, variables and summary statistics, and an outline of our research methodology. We then present the empirical results, and the final section of the paper provides our conclusions.

2.3 Related Literature

As a bricks-and-mortar asset class, real estate is highly exposed to physical climate risks, some more visible than others. According to Contat et al. (2024), these risks fall into two broad categories: acute or chronic. Acute risks, such as floods or wildfires, have immediate and clearly visible impacts on real estate markets. Chronic risks, such as temperature extremes or poor air quality, are typically less apparent and harder to quantify due to data and measurement limitations.

Existing literature on physical climate risks primarily focused on flood risks linked to natural disasters, such as hurricanes and climate-induced sea level rise. Harrison et al. (2001) show that residential properties in Florida experience price discounts when located within 100-year floodplains, with these discounts increasing after the National Flood Insurance Reform Act of 1994. Similarly, Addoum et al. (2024) and Ortega and Taşpınar (2018) find that Hurricane Sandy led to a persistent decline in property values, both commercial and residential, in New York, even in areas largely unaffected by the storm. This suggests that natural disasters can amplify perceived climate risk beyond directly impacted zones. After Hurricane Katrina, McKenzie and Levendis (2010) report a significant price premium for New Orleans homes located in less flood-prone areas. Likewise, Tyndall (2023) using a sample of residential properties on Long Island, finds that homes exposed to future sea level rise face a 1% appreciation discount compared to non-exposed properties while also triggering demand spillover effects. Supporting this trend, Bernstein et al. (2019) estimate that flood-affected properties sell at a 7% discount.

In addition to price effects, flood risk also impacts the liquidity of residential properties. Using search theory, Turnbull et al. (2013) argue that focusing solely on values and prices may underestimate actual flood risk, emphasizing the need to account for liquidity constraints in residential transactions. Beyond the equity side, where lower values, prices, and liquidity are observed, flood exposure also affects loan terms. Nguyen et al. (2022) find that lenders incorporate long-term sea level rise risk into mortgage pricing, independent of short-term natural hazards or borrower characteristics at loan origination. Similarly, Duanmu et al. (2022) report stronger risk pricing in counties with greater exposure to natural disasters, where lenders exhibit higher climate risk awareness. Despite this growing awareness in both equity and debt markets, Gourevitch et al. (2023) estimate, using a multivariate repeat-sales model, that U.S. residential properties exposed to flood risk remain overvalued by approximately US$121–US$237 billion, with coastal properties and low-income households disproportionally affected.

Wildfires have gained greater attention in the climate risk literature due to their rising frequency and severity in recent decades. Loomis (2004) was among the first to show that residential property values in areas spared by a significant wildfire declined by up to 15%, driven by both the loss of green space, which reduces amenity values, and heightened awareness of natural hazards. In areas affected by repeated wildfires, price decline can be even more severe, reaching up to 23% (Mueller et al., 2009). Using a difference-in-differences estimation, Götz et al. (2024) show that banks apply a mortgage interest margin premium for properties near wildfire events, averaging 13 basis points, and up to 22 basis points for low-income borrowers. Rising wildfire risk awareness also shifts homebuyers' preferences towards fire-resistant materials (Donovan et al., 2007). Baylis and Boomhower (2019) report that most U.S. federal and state wildfire mitigation goes toward protecting private homes, but note that housing subsidies aimed at affordability can inadvertently encourage development in high-risk areas, undermining wildfire risk reduction efforts.

Sinha and Cropper (2013) suggest that climate-related risks extend beyond natural hazards that cause direct physical damage to buildings. Specifically, physical climate risks that affect the amenity value of climate account for a substantial share of total climate-related damage in real estate markets. A prominent body of research demonstrates a positive relationship between amenity value and property prices, especially in relation to air quality (Chay & Greenstone, 2005; Choi et al., 2023; Cvijanović et al., 2024; Ridker & Henning, 1967; Zheng et al., 2014). However, air quality is shaped not only by climatic factors, such as air pressure, humidity, solar radiation, temperature and wind speed—but also by anthropogenic influences, including building energy use, industrial activity and traffic. This interplay complicates efforts to isolate the portion of air quality effects directly attributable to climate change. Roback (1982) was among the first to show that climatic factors alone, such as cloud cover, heating degree day (HDD) or snowfall, can influence house prices.

Research indicates that temperature has a significant impact on economic outcomes. Dell et al. (2012) and Dell et al. (2014) show that temperature shocks influence a range of national-level, socio-economic factors, including conflict, political stability and public health, as well as key macroeconomic indicators such as economic growth, industrial output and labor productivity. Focusing on income effects, Dell et al. (2009) find that the negative relationship between temperature and economic performance holds across countries, within countries and even at the state level.

Beyond macroeconomic effects, Bansal et al. (2016) show that systematic risk increases with long-term temperature variations, with the temperature-related risk premium for U.S. equities nearly doubling over the past 80 years. Similar patterns emerge in commercial real estate (CRE) markets. Using a repeat sales framework, Cvijanovic and Van de Minne (2023) show that asset-level returns are lower for properties in extreme-temperature locations, primarily due to higher cash flow volatility associated with climate risks. These findings align with Chiang et al. (2022), who argue that the significant negative relationship between abnormal temperature and CRE returns is driven more by growing investor awareness of climate risks than by location alone.

For residential properties, Cragg and Kahn (1997) find that willingness to pay for a temperate climate increases over an individual's life cycle. Their results suggest that hedonic pricing models may underestimate the value households place on climate stability and reduced annual variability. Semenenko and Yoo (2019), using weather station data near major global cities and capital regions, identify an inverse relationship between residential real estate returns and daily temperature volatility. Similarly, Butsic et al. (2011) find that declining snow reliability due to rising temperatures negatively affects house prices in major ski resorts across Canada and the U.S.

R. Y. M. Li et al. (2018) provide preliminary evidence that higher temperatures reduce housing estate prices in Hong Kong, with stronger effects in urbanized areas compared to non-urbanized locations with similar climates. More broadly, Albouy et al. (2016) find that U.S. households prefer an average temperature of 65°F (18.3°C) at the metropolitan statistical area (MSA) level and are willing to pay higher housing costs for climate comfort, showing a stronger aversion to excessive heat than to extreme cold. These preferences vary depending on a region's adaptive capacity. Extending this analysis, Klaiber et al. (2017) use four-kilometer resolution temperature data within a

Hausman-Taylor model and find that temperature mitigation efforts are capitalized into housing prices. They estimate a significant marginal willingness to pay $72 per month for each one-degree (F) reduction in outdoor temperatures. Notably, Cragg and Kahn (1997) also suggest that households value temperate climate more than is typically reflected in housing prices.

As noted by Contat et al. (2024) and reinforced by our review of the literature, existing research has largely focused on acute physical risks. In contrast, chronic risks, such as atmospheric and heat-related hazards, have received significantly less attention. While some studies have examined willingness to pay for temperature at national or state levels, to the best of our knowledge, no research has investigated heat-related risks in real estate markets at highly granular, intra-city scales that can reveal pricing effects at the neighborhood or individual property levels.

2.4 Data and Methodology

2.4.1 Housing Data

To investigate the effects of UHI exposure at a highly granular level, this study focuses on a single city. Berlin, Germany's capital, at the NUTS 3 level, serves as an ideal housing market for studying the impacts of UHI relevant to other mid-latitude cities worldwide. With a population of 3.89 million, it is among the most densely populated areas in Europe. Several factors make Berlin particularly suited to this study, including its heat-absorbing building stock (Dugord et al., 2014), 70% land coverage (Umweltbundesamt, 2024), limited green space and high levels of air pollution (European Environment Agency, 2024). Berlin also illustrates that even cities with a continental climate, typically associated with lower average temperatures, can experience significant UHI effects.

To capture long-term trends in both the residential property market and temperature development, the observation period spans 40 quarters from January 2014 to December 2023. The housing dataset is compiled from multiple data sources, including spatial data from OpenStreetMap[2], socioeconomic data from Growth from Knowledge (GfK)[3] and real estate data from VALUE market data[4]. VALUE market data aggregates

[2]See OpenStreetMap (2024). (https://www.openstreetmap.org).
[3]See GfK (2024). Growth from Knowledge. (https://www.gfk.com/home).
[4]See Value AG (2024). VALUE market data.

building-level data from over 100 listing platforms across Germany, enabling the collection of both continuous and categorical data, including prices and key hedonic characteristics. To ensure consistency in housing supply and demand perspectives, and to obtain a homogeneous sample, this study focuses exclusively on apartments, with valuation based on asking prices. In the German property market, especially in densely populated areas, asking prices generally align with final transaction prices, as negotiations are uncommon (Kolbe et al., 2021; Ahlfeldt et al., 2023).

The original dataset contained over 140 variables, including hedonic property characteristics and geographical points of interest (POIs), allowing for detailed property descriptions. During data-cleaning, observations with missing key variables were excluded, and numerical outliers were removed using the 98$^{\text{th}}$ interquartile range (IQR). The final sample consists of 169,139 observations and 28 variables, enabling each property to be identified through a combination of hedonic and geographic attributes. Demographic data at the postal code level was added to capture housing demand dynamics, as higher population density correlates with stronger demand (Glaeser & Gottlieb, 2006) and greater traffic intensity (H. Li et al., 2018). Specific POI variables, such as proximity to the nearest park, were included to assess the impact of green space on property values. Each property was georeferenced using longitude and latitude coordinates, allowing for precise linkage to temperature data.

2.4.2 Urban Heat Island Data

Temperature data were provided by Meteoblue[5], offering citywide coverage of Berlin on a 30 m × 30 m grid from 2014–2023 and yielding more than 10 billion observations. The series measures near-surface air temperature (2 m above ground).[6] Because near-surface air temperature better reflects human-perceived heat exposure, it is more relevant for assessing impacts on property prices.

This study follows the framework of Oke (1982) to capture both day- and nighttime heat dynamics. As summarized in Figure 2.1, direct solar radiation and the differential warming of surface materials generate sizeable daytime temperature differences—a direct measure of heat exposure. At night, these same factors cause buildings to retain stored heat and cool less efficiently than their surroundings. To capture these

[5]See Meteoblue AG (2024). Weather API. (https://content.meteoblue.com/de).

[6]For simplicity, we use the generic term UHI throughout, but our analysis focuses on the atmospheric urban heat island (AUHI), not the surface urban heat island (SUHI) effect.

temperature differences, and the resulting spatial UHI effects, air temperatures (°C) were recorded twice daily at 4 a.m. and 1 p.m. The selection of these two time points is rooted in existing literature (see e.g., Arnfield (2003), Oke (2002), Voogt and Oke (2003)).

Next, we constructed the UHI variable. Traditionally, UHI intensity is measured as the temperature difference between an urban site and a rural reference point outside the city (Oke, 1973). Instead, we use a within-city reference: for each timestamp (4 a.m. and 1 p.m.), the Berlin-wide minimum temperature serves as the reference value. UHI intensity was then calculated as the difference between the local temperature for an asset *i* and the citywide minimum at time *t*.

$$\mathrm{UHI}_{it} = \mathrm{Temp}_{it} - \min(\mathrm{Temp}_t) \tag{2.1}$$

Finally, we georeferenced each temperature observation and matched it to individual property price records using precise latitude-longitude coordinates. This provided high spatial granularity and addressed common data limitations in previous studies.

Two factors motivate our within-city reference. First, the exceptionally high spatial resolution enables a more localized, less biased estimation of UHI effects. Second, a single rural reference point can introduce selection bias: wind can carry urban heat into nearby rural areas, making the urban-rural transition gradual rather than abrupt (Oke, 1982). Compounding this, no aggregated rural temperature series with sufficient temporal resolution (4 a.m. and 1 p.m.) was available at the state or regional level, further justifying our approach.

2.4.3 Summary Statistics

Table 2.1 reports descriptive statistics for all variables used in the models, covering observations from the entire year, including both winter and summer months. To reduce distortions caused by outliers and right-skewness, we log-transformed *price*, *apartment size* and *household income*. Temperature variables at 4 a.m. and 1 p.m. were included to capture UHI intensity: *UHI 4am* and *UHI 1pm*.

UHI intensity ranges from 0.70 °C (33.26 °F) to 6.07 °C (42.93 °F) at night (4 a.m.) and from 0.97 °C (33.75 °F) to 6.75 °C (44.15 °F) during the day (1 p.m.). These distributions indicate that daytime urban heating is generally stronger and more spatially variable across neighborhoods. Nighttime UHI effects are also pronounced, with some hotspots remaining up to 6.07 °C (42.93 °F) warmer than the coolest area.

On average, UHI intensity measures 2.32 °C (36.18 °F) at 4 a.m. and intensifies to 2.87 °C (37.17 °F) at 1 p.m. These values correspond to mean absolute temperatures of 8.87 °C (47.97 °F) (4 a.m.) and 14.46 °C (57.99 °F) (1 p.m.), a pattern consistent with previous studies (Iodice et al., 2024). The contrast in minimum daily temperatures further reflects this dynamic, with –14.13 °C (6.57 °F) recorded at night compared to –10.91 °C (12.36 °F) during the day.

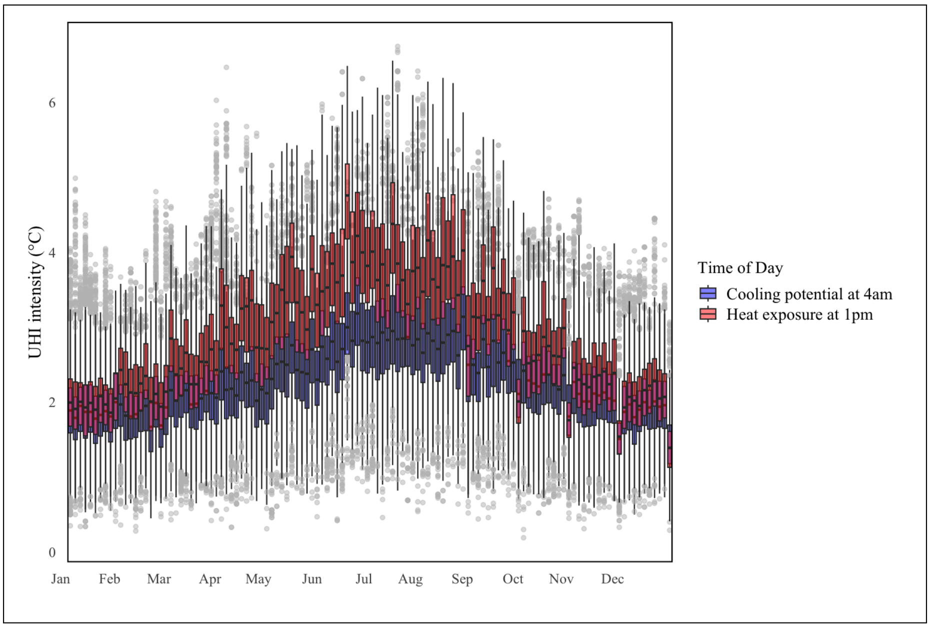
Table 2.1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Q5	Median	Q95	Max
Price	359372.99	244244.91	16500.00	95000.00	292536.00	870000.00	1440000.00
Log price	12.58	0.66	9.71	11.46	12.59	13.68	14.18
Size	79.78	34.89	8.22	36.00	71.33	150.00	210.00
Log size	4.29	0.43	2.11	3.58	4.27	5.01	5.35
Rooms	2.66	1.08	1.00	1.00	2.50	5.00	6.00
Age	70.45	44.57	-2.00	4.00	68.00	124.00	124.00
School distance	0.30	0.19	0.00	0.07	0.26	0.69	1.20
Kindergarten distance	0.21	0.15	0.00	0.05	0.17	0.54	1.26
University distance	2.14	1.85	0.01	0.34	1.56	6.12	19.93
Restaurant distance	0.20	0.16	0.00	0.03	0.15	0.54	0.95
Supermarket distance	0.27	0.18	0.00	0.05	0.24	0.62	1.23
Kiosk distance	0.51	0.53	0.00	0.07	0.34	1.51	5.01
Park distance	0.27	0.17	0.00	0.07	0.24	0.58	1.38
Playground distance	0.20	0.14	0.00	0.05	0.17	0.49	0.80
CBD distance	7.41	4.23	0.02	1.87	6.85	15.00	26.45
Bus distance	0.18	0.11	0.00	0.03	0.15	0.39	0.65
Tram distance	3.47	3.50	0.00	0.11	2.62	10.54	22.70
Railway distance	1.07	0.75	0.01	0.23	0.90	2.49	5.03
Doctors distance	0.48	0.42	0.00	0.07	0.36	1.29	3.38
Pharmacy distance	0.33	0.23	0.00	0.06	0.28	0.81	1.79
Hospital distance	1.50	0.95	0.01	0.35	1.33	3.39	7.44
Longitude	13.38	0.09	13.09	13.24	13.37	13.54	13.67
Latitude	52.50	0.05	52.37	52.42	52.50	52.58	52.67
Population per postal code	20398.21	7050.59	4295.00	10364.00	19557.00	32566.00	44236.00
Household income	37378.53	5890.10	26473.78	29547.39	36268.72	48586.89	70799.97
Log Income per household	10.52	0.15	10.18	10.29	10.50	10.79	11.17
Temp 4am	8.87	6.56	-14.13	-1.46	9.11	19.13	25.46
Temp 1pm	14.46	8.51	-10.91	1.47	14.29	28.25	38.62
UHI 4am	2.32	0.70	0.19	1.26	2.27	3.55	6.07
UHI 1pm	2.87	0.97	0.29	1.46	2.75	4.62	6.75

The table summarizes the descriptive statistics for the variables used in this analysis, covering the entire observation period. For each variable, we report the mean, standard deviation (Std.Dev.), minimum (Min.), the 5th percentile (Q5), the median, the 95th percentile (Q95), and the maximum (Max.). To reduce the influence of extreme values, outliers in numerical variables were removed based on the 98th interquartile range.

Figure 2.2 presents the development of the UHI effect across the observation period in monthly intervals. Consistent and systematic differences between daytime and nighttime temperatures are clearly visible, underscoring the seasonality of the UHI effect. UHI intensity increases during warmer months, as reflected in higher quartile values and more significant variance in temperature differences. These findings are consistent with Xi et al. (2024), who reported that both the distributions and intensities of UHI effects peak during summer. Quantile distributions further reveal a broader spread of temperature at 1 p.m. compared to 4 a.m. during these warmer months. Seasonal fluctuations are also reflected in the average UHI intensity values, as the differences between 1 p.m. and 4 a.m. are greater in summer than those observed in winter. The cooling potential of locations is therefore more pronounced during summer months, especially in areas that are less affected by UHI dynamics. In contrast, UHI effects are lower in winter in all statistical measures such as quantiles, means, and variances, due to more uniform and stable urban temperatures.

Figure 2.2: Boxplot of UHI Intensity across the Sample Period



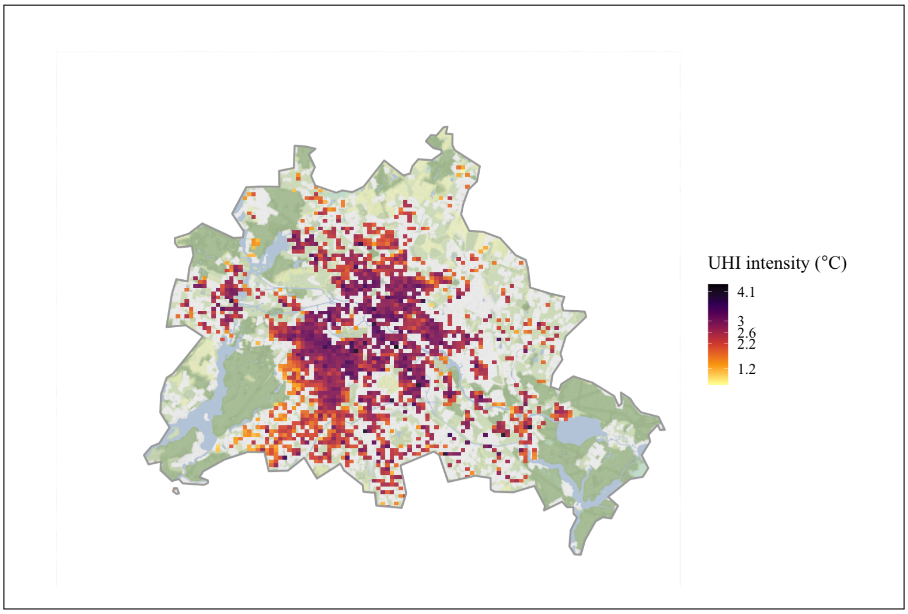
The figure illustrates the distribution of UHI intensity measured at 4 a.m. and 1 p.m. across monthly intervals from 2014 to 2023. The boxplots display temperature variations relative to the minimum temperature in each timeframe, with red indicating 1 p.m. (daytime) values and blue indicating 4 a.m. (nighttime) values. Grey dots indicate statistical outliers. All temperature values are expressed in degrees Celcius (°C).

Figures 2.3a, 2.3b, 2.4a and 2.4b show the temporal and spatial distribution of UHI intensity in Berlin during the summer months (April-September) of 2014-2016 and 2020-2023, using temperatures recorded at 4 a.m. and 1 p.m. Pronounced UHI effects emerge: intensities peak in the inner-city, while suburban and rural zones are comparatively cooler, consistent with the classic urban-rural heat gradient described by Oke (1982). In addition to highlighting differences between urban and non-urban zones, the figure also reveals substantial intra-city variations in UHI intensity. These localized differences reflect Berlin's polycentric form and neighborhood-level differences in heat accumulation down to the scale of individual buildings.

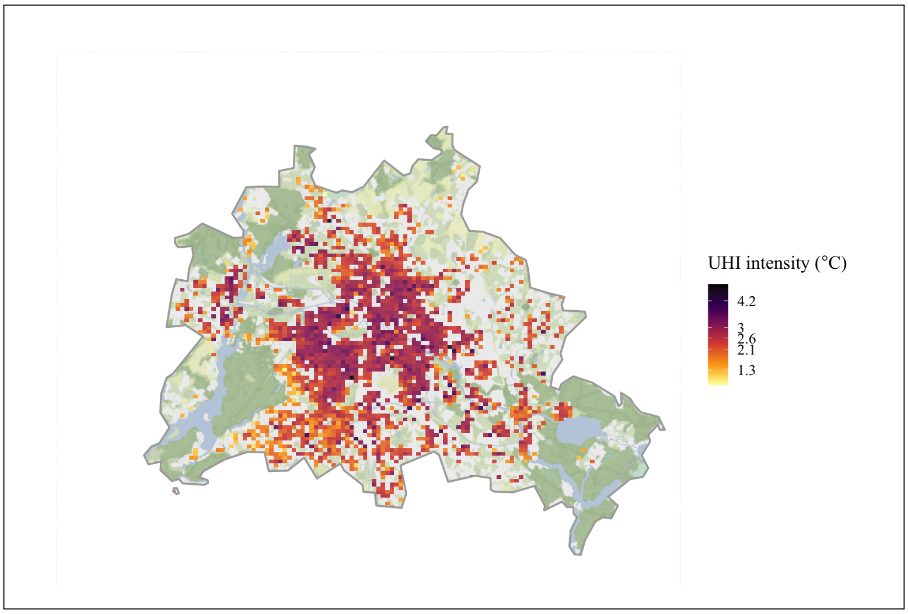
At 4 a.m., the spatial distribution of temperatures shows UHI effects of up to 4 °C (39.2 °F), especially in central districts and densely built areas. A clear cooling gradient emerges, with suburban zones benefiting most from overnight temperature drops. Still, the urban core retains substantial heat driven by extensive impervious surface coverage. In some locations, cooling relative to daytime is minimal, indicating limited overnight cooling potential.

Consistent with the summary statistics, the maps show that UHI intensity increases citywide at 1 p.m., with the largest effects—up to 5 °C (41.0 °F)—in the inner city. Elevated temperatures spread more broadly during the day, likely driven by direct solar radiation and anthropogenic heat emissions. The temporal comparison shows that UHI intensity has become more widespread. Suburban and rural areas exhibit rising, though still lower UHI effects, while more urbanized regions display persistence, higher UHIs with an outward expansion from Berlin's center.

Figure 2.3: Maps of the UHI Intensity at 4 a.m. across Berlin over Time



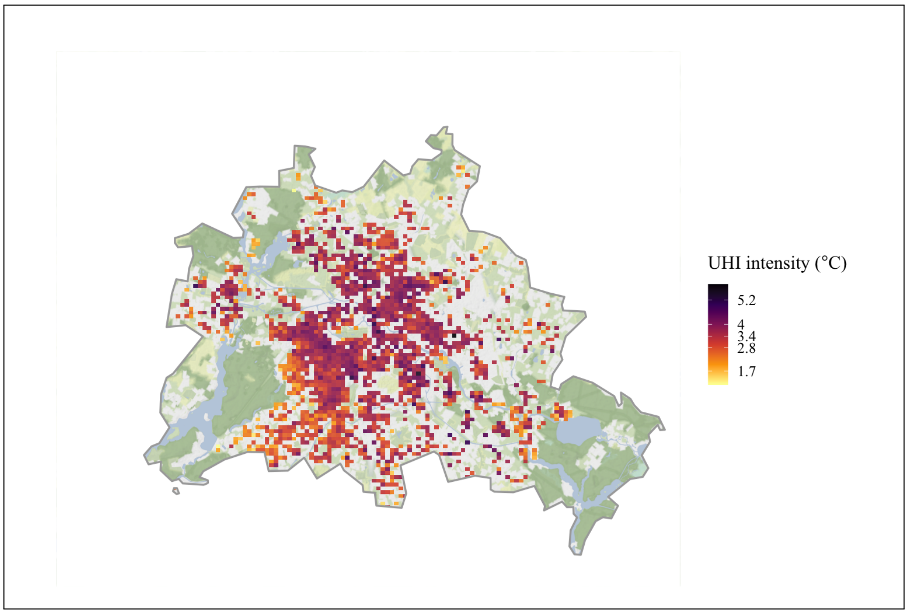
(a) 2014–2016



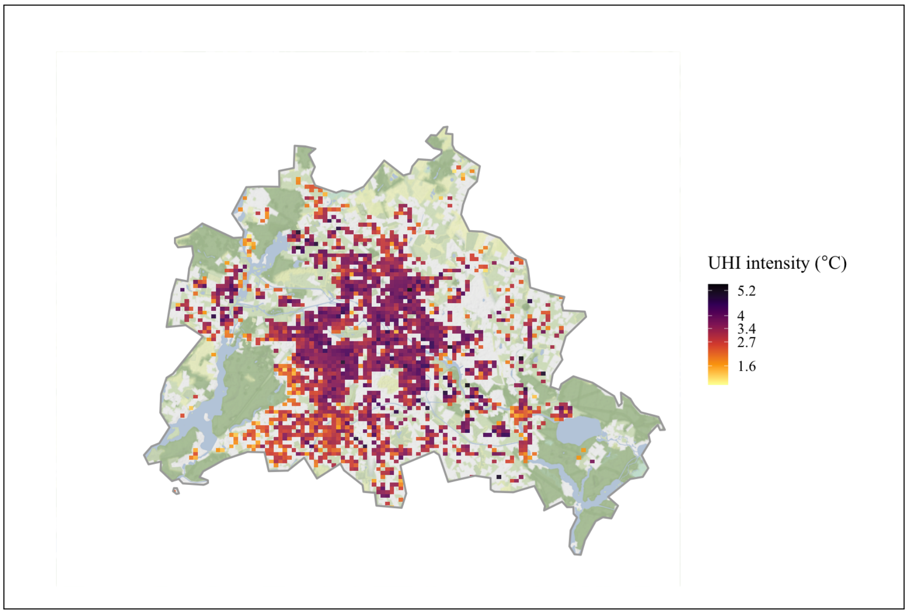
(b) 2020–2023

The figures illustrate the spatial distribution of UHI intensity at 4:00 a.m. Figure (a) covers 2014–2016; Figure (b), 2020–2023. Each grid cell represents temperature differences (°C) relative to the minimum observed temperature. The legend shows values in degrees Celsius, ranging from –0.5 °C to 3.5 °C in (a) and –0.5 °C to 4.5 °C in (b). Colors range from yellow (lower differences) through orange/red (medium) to violet (higher).

Figure 2.4: Maps of the UHI Intensity at 1 p.m. across Berlin over Time



(a) 2014–2016



(b) 2020–2023

The figures illustrate the spatial distribution of UHI intensity at 1:00 p.m. Figure (a) covers 2014–2016 ; Figure (b), 2020–2023. Each grid cell represents temperature differences (°C) relative to the minimum observed temperature. The legend shows values in degrees Celsius, ranging from –0.5 °C to 4.5 °C in (a) and –0.5 °C to 5.0 °C in (b). Color ranges from yellow (lower differences) through orange/red (medium) to violet (higher).

2.4.4 Research Methodologies

As a first step, we establish a benchmark model using an ordinary least squares (OLS) regression, a widely applied approach in studies of climate risks and real estate prices (Harrison et al., 2001; R. Y. M. Li et al., 2018; Loomis, 2004; Ortega & Taṣpınar, 2018). Despite widespread application, prior research suggests that the relationship between dependent and independent variables should not be assumed universally (Conroy & Milosch, 2011; McKenzie & Levendis, 2010). As a result, OLS can miss the complex, nonlinear relationships that characterize climate-related risk.

To address these limitations, we employ a GAM, a semi-parametric approach incorporating penalized smooth terms, as pioneered by Hastie and Tibshirani (1987). GAMs allow covariates to take nonlinear functional structure, reducing error variance and improving predictive accuracy (Eilers & Marx, 1996). Owing to this flexibility, GAMs have become increasingly popular in real estate price forecasting (Bin, 2004).

$$log(\hat{P}_{ijt}) = X_{ijt}\beta + Z_{jt}\delta + \mu_t\theta + f(U\tilde{H}I_{it}) + f(\tilde{X}_{ijt}) + \varepsilon_{ijt} \tag{2.2}$$

Equation (2.2) estimates the property prices $\hat{P}$ for an asset i at time t. We estimate separate models for 4 a.m. and 1 p.m. to capture temporal variation in the UHI effect. The model form is identical across specifications; each uses a temperature regressor $U\tilde{H}I_{it}$ measured at either 1 p.m. or 4 a.m.

Determinants are structured as follows: Location-specific covariates Z_{jt} capture spatial effects and help mitigate the unobserved serial error component, with j indexing the postal code. Time fixed effects are included via monthly dummies (μ_t) for the listing period. The property attributes, including both continuous and binary hedonic characteristics, are represented by the matrix X_{ijt}. Nonlinear effects enter via splines $f(\tilde{X}_{ijt})$ by using a predefined set of nonlinear functions. The complex relationships between property characteristics, including floor area, number of rooms and price, underscore the need for an advanced nonlinear modeling approach. Additionally, nonlinear transformations of POIs help to reflect spatial effects on property prices. The error term ε_{ijt} captures unexplained variations, and β, δ, and θ denote the vectors of estimated coefficients.

To assess diurnal variations in UHI effects, we estimate two distinct model specifications: one capturing nighttime heat retention (limited overnight cooling potential) (*UHI 4am*), the other measures daytime heat exposure (*UHI 1pm*). Both include the same covariates, nonlinear terms and spatial controls, differing only in their UHI variables.

Additional models extend the baseline by introducing interaction terms of the general form $f(\tilde{UHI}_{it} \times Z_{ij,t})$. Specifically, Model 2 defines $Z_{ij,t}$ as a vector of *monthly dummies* to capture seasonal heterogeneity. Model 3 sets $Z_{ij,t}$ to *household income* terciles to estimate income-specific sensitivities; and Models 4 and 5 use *park distance* and *CBD distance*, respectively, to capture spatial variation. This structure is applied simultaneously for the models at 4 a.m. and 1 p.m., enabling a direct comparison of nighttime and daytime UHI pricing effects while holding other factors constant. Separate estimation is warranted because the two measures are strongly collinear.

To analyze the effects of UHI intensity and their economic implications, we compute several key performance indicators (KPIs) (see Appendix for formulas). The cumulative growth rate captures the total long-term price change, while the average annual growth summarizes the mean year-on-year (YoY) increase. Volatility and risk-adjusted performance are summarized by the risk indicator (standard deviation of YoY growth) and the return-to-risk ratio. The compound annual growth rate (CAGR) represents the smoothed annualized growth over the observation period, allowing for direct comparisons across UHI intensity groups.

2.5 Empirical Results

Tables 2.2 and 2.3 report the GAM estimates for 1 p.m. and 4 a.m. based on the annual dataset. Each table also contains the extended specifications used to isolate specific effects. Both baseline models achieve an adjusted R^2 of 0.888, indicating strong explanatory power.[7] Also, the extended models with additional interaction terms show similar Adj. R^2 values, and thus prove a consistent explanatory power, so the interactions are included to isolate effects rather than improve overall fit. In addition, the models exhibit similar error values and thus comparable predictive power (see Table 2.4a and 2.4b).

[7] The OLS reference model provides an adj. R^2 of 0.851; see the error matrix for a detailed model comparison.

Table 2.2: GAM Results for 4 a.m. UHI Intensity

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
(Intercept)	11.949***	0.005	11.402***	0.017	4.675***	0.003	11.950***	0.005	11.949***	0.005
Floors	0.013***	0.000	0.013***	0.000	0.013***	0.000	0.013***	0.000	0.013***	0.000
Kitchen	0.063***	0.001	0.063***	0.001	0.063***	0.001	0.063***	0.001	0.062***	0.001
Balcony/Terrace	0.050***	0.001	0.050***	0.001	0.050***	0.001	0.050***	0.001	0.049***	0.001
Parking	0.044***	0.001	0.044***	0.001	0.044***	0.001	0.044***	0.001	0.044***	0.001
Retrofitted	0.065***	0.001	0.065***	0.001	0.065***	0.001	0.064***	0.001	0.065***	0.001
First occupancy	0.198***	0.002	0.198***	0.002	0.198***	0.002	0.198***	0.002	0.198***	0.002
Summer	0.490***	0.005								
Time FE (YYYYMM)	yes		yes		yes		yes		yes	
Smooth terms										
Log size	8.592***	18462.9	8.596***	18426.2	8.535***	18443.16	8.585***	18452.49	8.592***	18440.83
Rooms	8.940***	57.430	8.942***	57.376	8.943***	57.091	8.943***	57.175	8.933***	56.730
Age	8.900***	1933.51	8.906***	1930.23	8.898***	1940.65	8.896***	1936.21	8.899***	1926.92
School distance	8.918***	29.109	8.911***	28.281	8.931***	32.938	8.900***	29.079	8.926***	27.697
Kindergarten distance	8.819***	30.881	8.816***	30.268	8.814***	31.924	8.791***	30.708	8.834***	31.144
Restaurant distance	8.762***	43.452	8.733***	42.365	8.758***	48.177	8.735***	43.163	8.687***	43.606
Supermarket distance	8.764***	21.434	8.768***	20.972	8.729***	23.135	8.754***	21.568	8.720***	20.547
Kiosk distance	7.194***	15.915	7.248***	14.870	7.682***	14.476	7.008***	16.412	7.468***	16.766
Park distance	8.613***	24.977	8.570***	23.727	8.482***	26.652	8.385***	10.533	8.477***	22.656
Playground distance	8.861***	17.236	8.857***	16.984	8.845***	19.980	8.847***	17.927	8.861***	15.037
CBD distance	8.923***	110.004	8.929***	108.467	8.914***	110.540	8.921***	110.157	8.992***	73.151
Bus distance	8.744***	12.000	8.761***	11.820	8.879***	13.521	8.703***	11.802	8.716***	13.631
Hospital distance	8.959***	22.065	8.993***	23.327	8.960***	23.462	8.991***	22.204	8.958***	21.278
s(Log income per hh)	8.792***	116.203	8.780***	123.375			8.784***	117.917	8.740***	118.407
Latitude, Longitude	28.842***	1253.3	28.812***	1243.75	28.908***	1243.34	28.860***	1249.36	28.943***	1218.75
UHI 4 am	6.692***	9.708	7.321***	4228.63	5.500***	459435.5	5.668	0.945	6.644	1.946
UHI 4 am × YYYYMM										
UHI 4 am × Income quantile										
UHI 4 am, Park							8.585***	18452.49		
UHI 4 am, CBD									8.592***	18440.83
Adj. R^2	0.888		0.888		0.888		0.888		0.888	
Deviance explained (%)	88.8		88.9		88.8		88.8		88.8	
AIC	-31133.3		-31303.2		-30712.8		-31205.9		-31334.0	
N	169 139		169 139		169 139		169 139		169 139	

The table reports GAM estimates for log(price) using five specifications shown side by side. Parametric terms (top panel) list coefficients (Est.), standard errors (SE), p-values (p) and significance (sig). Smooth terms (middle panel) are reported with effective degrees of freedom (EDF), the approximate F statistic, and p-values for the joint nonlinearity tests. A two–dimensional spatial surface $s(\text{Latitude}, \text{Longitude})$ captures unobserved spatial variation; distances to amenities (POIs) enter as smooths to allow nonlinear effects. Monthly dummies (Month FE (YYYYMM)) indicate time fixed effects. Interaction rows are ordered to mirror the model sequence and display "yes" when the term is present. Model 1 is the baseline with $s(\text{UHI 4 am})$ (plus a summer dummy); Model 2 adds the parametric interaction UHI ×Month; Model 3 adds UHI ×Income quantile; Model 4 includes the tensor product $te(\text{UHI 4 am}, \text{Park distance})$; Model 5 includes $te(\text{UHI 4 am}, \text{CBD distance})$. The bottom panel summarizes fit measures: adjusted R^2, deviance explained (in %), Akaike Information Criterion (AIC), and sample size N. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$.

Table 2.3: GAM Results for 1 p.m. UHI Intensity

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
(Intercept)	11.945***	0.005	11.147***	0.017	3.854***	0.002	11.945***	0.005	11.945***	0.005
Floors	0.013***	0.000	0.013***	0.000	0.013***	0.000	0.013***	0.000	0.013***	0.000
Kitchen	0.063***	0.001	0.063***	0.001	0.063***	0.001	0.063***	0.001	0.062***	0.001
Balcony/Terrace	0.050***	0.001	0.050***	0.001	0.050***	0.001	0.050***	0.001	0.049***	0.001
Parking	0.044***	0.001	0.044***	0.001	0.044***	0.001	0.044***	0.001	0.044***	0.001
Retrofitted	0.065***	0.001	0.065***	0.001	0.065***	0.001	0.065***	0.001	0.064***	0.001
First occupancy	0.198***	0.002	0.198***	0.002	0.198***	0.002	0.198***	0.002	0.198***	0.002
Summer	0.496***	0.005								
Month FE (YYYYMM)	yes		yes		yes		yes		yes	
Smooth terms										
Log size	8.605***	18463.4	8.595***	18451.6	8.570***	18436.4	8.571***	18458.05	8.595***	18442.92
Rooms	8.930***	57.485	8.943***	58.004	8.942***	57.318	8.942***	57.339	8.937***	57.006
Age	8.898***	1933.06	8.905***	1927.39	8.898***	1939.97	8.904***	1936.15	8.903***	1926.12
School distance	8.918***	28.731	8.897***	28.055	8.910***	32.522	8.927***	29.142	8.932***	27.340
Kindergarten distance	8.929***	31.333	8.773***	29.119	8.781***	31.574	8.805***	30.257	8.850***	31.008
Restaurant distance	8.762***	43.077	8.730***	42.780	8.739***	47.613	8.781***	43.039	8.693***	43.650
Supermarket distance	8.766***	21.492	8.742***	21.048	8.705***	22.824	8.795***	21.313	8.741***	20.587
Kiosk distance	7.170***	16.016	6.928***	15.493	7.700***	14.723	6.988***	16.189	7.319***	16.848
Park distance	8.615***	24.883	8.566***	23.643	8.503***	27.076	8.955***	17.372	8.455***	22.427
Playground distance	8.851***	17.457	8.842***	16.945	8.813***	20.245	8.855***	18.278	8.879***	15.508
CBD distance	8.916***	111.123	8.924***	110.542	8.918***	112.226	8.926***	110.227	8.950***	72.698
Bus distance	8.742***	12.012	8.733***	11.705	8.765***	13.501	8.735***	12.309	8.703***	13.958
Hospital distance	8.958***	22.302	8.992***	23.279	8.990***	23.996	8.970***	22.379	8.961***	21.497
Log income per household	8.795***	116.169	8.784***	119.540			8.789***	117.487	8.756***	118.558
Latitude, Longitude	28.844***	1256.98	28.797***	1241.83	28.901***	1249.86	28.899***	1243.50	28.829***	1237.89
UHI 1 pm	2.867***	23.785	4.502***	10102.5	2.855***	1095923.2	1.002	15.915	5.268	1.235
UHI 1 pm × YYYYMM			yes							
UHI 1 pm × Income quantile							yes			
UHI 1 pm, Park							8.571***	18458.04		
UHI 1 pm, CBD									8.595***	18442.92
Adj. R^2	0.888		0.888		0.888		0.888		0.888	
Deviance explained (%)	88.8		88.9		88.8		88.8		88.8	
AIC	-31133.3		-31303.2		-30712.8		-31205.9		-31334.0	
N	169 139		169 139		169 139		169 139		169 139	

The table reports GAM estimates for log(price) using five specifications shown side by side. Parametric terms (top panel) list coefficients (Est.), standard errors (SE), p-values (p) and significance (sig). Smooth terms (middle panel) are reported with effective degrees of freedom (EDF), the approximate F statistic, and p-values for the joint nonlinearity tests. A two–dimensional spatial surface $s(\text{Latitude}, \text{Longitude})$ captures unobserved spatial variation; distances to amenities (POIs) enter as smooths to allow nonlinear effects. Monthly dummies (Month FE (YYYYMM)") indicate time fixed effects. Interaction rows are ordered to mirror the model sequence and display yes" when the term is present. Model 1 is the baseline with $s(\text{UHI 1 pm})$ (plus a summer dummy); Model 2 adds the parametric interaction UHI ×Month; Model 3 adds UHI ×Income quantile; Model 4 includes the tensor product $te(\text{UHI 1 pm}, \text{Park distance})$; Model 5 includes $te(\text{UHI 1 pm}, \text{CBD distance})$. The bottom panel summarizes fit measures: adjusted R^2, deviance explained (in %), Akaike Information Criterion (AICr), and sample size N. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$, $\cdot p < 0.10$.

Table 2.4: Model Performance Comparison Metrics

(a) 4 a.m.

Model	Adj. R^2	MAE	MAPE	MdAPE	RMSE	RRSE
OLS	85.1	68,547.60	20.33%	16.01%	106,117.57	0.434
Model 1	88.8	59,463.93	17.42%	13.51%	93,622.46	0.383
Model 2	88.9	59,373.53	17.40%	13.47%	93,460.71	0.383
Model 3	88.8	59,557.44	17.45%	13.53%	93,698.62	0.384
Model 4	88.8	59,451.29	17.42%	13.47%	93,599.98	0.383
Model 5	88.8	59,438.21	17.42%	13.50%	93,592.37	0.383

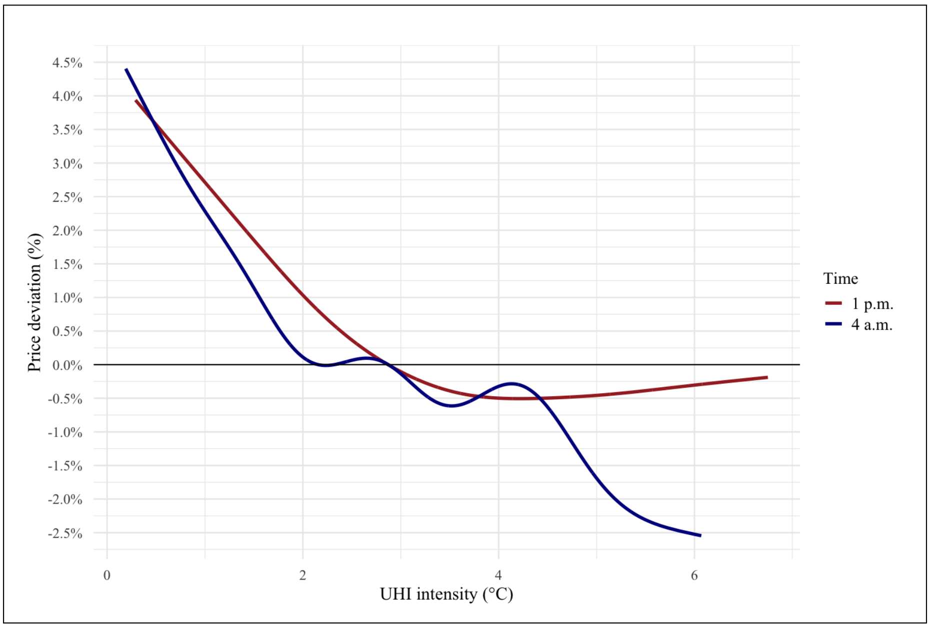
(b) 1 p.m.

Model	Adj. R^2	MAE	MAPE	MdAPE	RMSE	RRSE
OLS	85.1	68,550.80	20.33%	16.01%	106,108.65	0.434
Model 1	88.8	59,454.46	17.42%	13.50%	93,607.48	0.383
Model 2	88.9	59,364.42	17.40%	13.47%	93,445.60	0.383
Model 3	88.8	59,548.93	17.45%	13.53%	93,695.84	0.384
Model 4	88.8	59,445.17	17.42%	13.49%	93,590.56	0.383
Model 5	88.8	59,429.01	17.41%	13.49%	93,564.34	0.383

The tables report error metrics across the OLS Model and the five GAM model specifications, each estimated for nighttime and daytime UHI measurements. The adj. R^2 is also represented in Tables 2.2 and 2.3. All error indicators are calculated on the original property price scale. The mean absolute error (MAE) captures the average magnitude of prediction errors, while the mean absolute percentage error (MAPE) and the median absolute percentage error (MdAPE) express error magnitudes in relative terms. The root mean squared error (RMSE) reflects the quadratic average of residuals, emphasizing larger deviations, and the relative root squared error (RRSE) normalizes model performance against a naive benchmark.

Figures 2.5 show percentage price deviations as a function of the local UHI effect, calculated relative to the Berlin-wide mean UHI intensity at 4 a.m. and 1 p.m. These figures visualize how property prices adjust to localized thermal exposure. At night (4 a.m.), effects are pronounced at both ends of the distribution: properties in cooler microclimates (below average temperatures) earn premiums of up to 4.5%, whereas above-average UHI exposure leads to increasing discounts, reaching up to -2.5% at the highest observed differences. However, around the average temperature difference of 2.32 °C (36.18 °F) the price deviations are minor and the curve is relatively flat, indicating no material premiums near average UHI levels. This indicates a thermal tolerance zone, with deviations beyond it producing measurable pricing effects.

Figure 2.5: Price Deviation as a Function of UHI Intensity

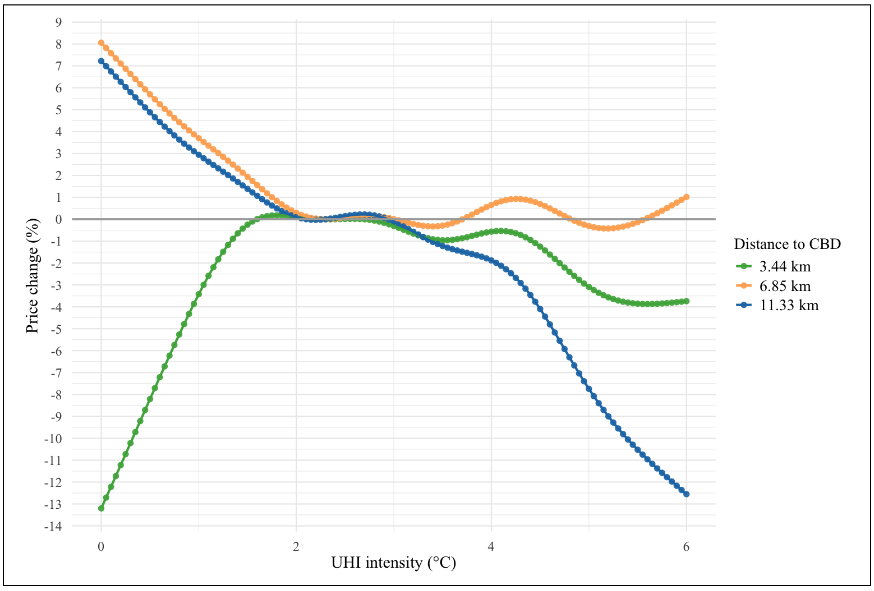


The figure illustrates the estimated property price deviation (%) as a function of UHI intensity (°C), measured at 1 p.m. (red line) and 4 a.m. (blue line). The x-axis represents UHI intensity in degrees Celsius, calculated as the deviation from the minimum observed temperature. The y-axis shows the predicted percentage change in property prices. The reference point for the price effect is the average UHI intensity, which corresponds to 2.32 °C at 1 p.m. and 2.78 °C at 4 a.m., indicated by the zero line on the y-axis. Estimates are derived from the semi-parametric GAM model 1, with smooth functions fitted separately for daytime and nighttime observations.

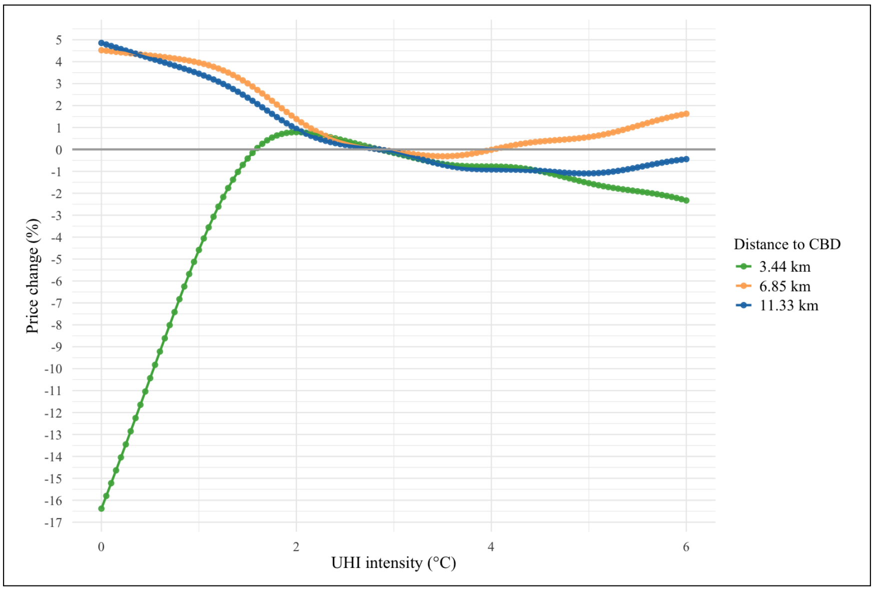
For daytime heat exposure (1 p.m.), the price response is more continuous and gradual. Properties in cooler-than-average locations (UHI $<$ 2.87 °C; 37.17 °F) earn consistent price premiums, reaching up to 4% at the lowest UHI levels. This pattern aligns with Klaiber et al. (2017), who demonstrates that even a (1.0 °F) change in ambient temperature can significantly affect housing demand and marginal willingness to pay. Conversely, above-average daytime UHI values are associated with modest price discounts that widen to around -0.5% at the upper end of the temperature spectrum. This flat sloping curve suggests a linear, predictable market response to midday thermal discomfort. Locations with cooler-than-average temperatures are characterized by a price premium. In contrast, daytime effects are smaller than nighttime effects, likely because household occupancy, and thus exposure, is higher at night.

The statistical significance of the monthly fixed effects captures both intra-seasonal price patterns and the broader upward trend in property prices over the past decade. Spatial POI variables also matter: proximity to parks or green spaces and distance from the CBD—used as a proxy for urban morphology and density—are key drivers of price variations. As shown in the Appendix correlation table, distance to the CBD has one of the strongest correlations with both UHI measures (-0.30 at 4 a.m. and -0.23 at 1 p.m.), highlighting the role of dense, impervious urban development in generating localized UHI hotspots. To capture this in our analysis, interaction terms between UHI intensity and distance to CBD/park were included, reflecting the price response to the distance to the POIs. These findings align with prior research (H. Li et al., 2018). Centrally located, high-demand neighborhoods, often characterized by high-rise structures and limited green infrastructure, absorb and retain more heat by day and cool more slowly at night. This pattern is central to Berlin's distinct UHI dynamics.

Figure 2.6: Price as a Function of UHI Intensities and Distance to CBD



(a) 4 a.m.



(b) 1 p.m.

The figures illustrate the relationship between UHI intensity and estimated property price changes. Figure (a) shows results for 4 a.m., and Figure (b) for 1 p.m. Property price changes (%) are plotted against UHI intensity (°C), measured relative to the minimum observed temperature. Price effects are estimated based on Model 5, which includes an interaction term between UHI intensity and CBD distance. Distances to the CBD are grouped into quantile-based categories with thresholds at 3.44 km, 6.85 km, and 11.33 km.

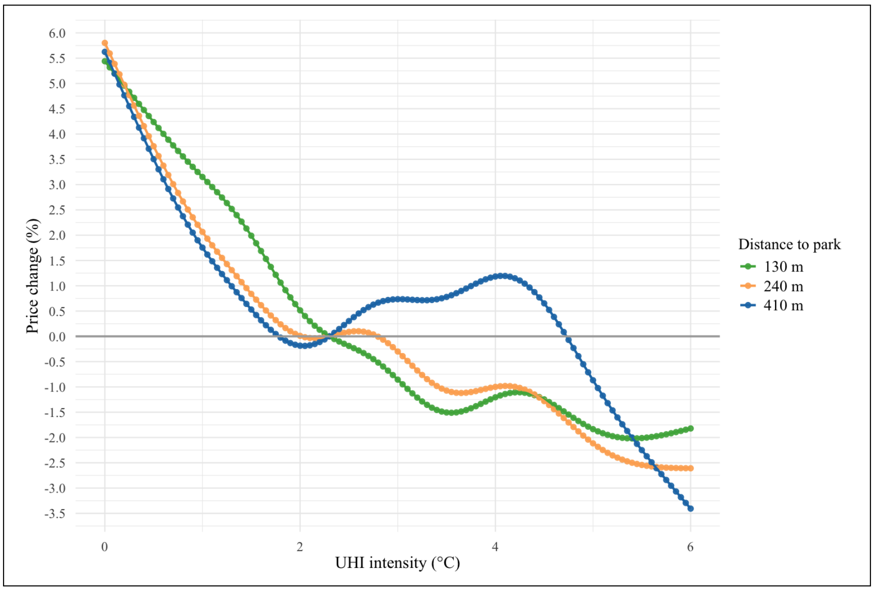
Figure 2.6a shows the price deviation depending on UHI intensity at night and distance to the CBD. Market effects vary by distance to the city center. Under below-average UHI, central locations (3.44 km) show discounts, while midrange (6.85 km) and peripheral (11.33 km) locations earn price premiums. However, as UHI intensities increase, peripheral locations in particular experience the largest price reductions. By contrast, central locations and those within 7 km of the CBD remain relatively flat and then develop neutral to slightly positive. Central locations show greater urban resilience: the combination of dense development, robust technical infrastructure (including building cooling, insulation, construction quality) and a stronger land-use mix helps mitigate price losses as UHI exposure rises. By contrast, peripheral locations are particularly vulnerable to extreme nighttime heat. In more remote areas, above-average nighttime temperatures are priced as a significantly negative factor.

Compared with nighttime patterns, daytime exposure shows that prices near the CBD are susceptible to changes around the average UHI value (Figure 2.6b). Above roughly 2 °C to 3 °C, prices rise slightly before falling moderately as UHI intensifies, suggesting a temporary resilience phase in which heat is perceived but not yet penalized in pricing. Peripheral areas are less sensitive to daytime heat; unlike at night, they exhibit no value loss and only moderate price sensitivity overall. These differences suggest that daytime heat is seen as less of a disadvantage in peripheral areas, perhaps because it is perceived as less intense or more manageable through individual coping strategies. By contrast, central locations see more pronounced price declines despite potential resilience mechanisms, indicating higher expectations for urban neighborhoods.

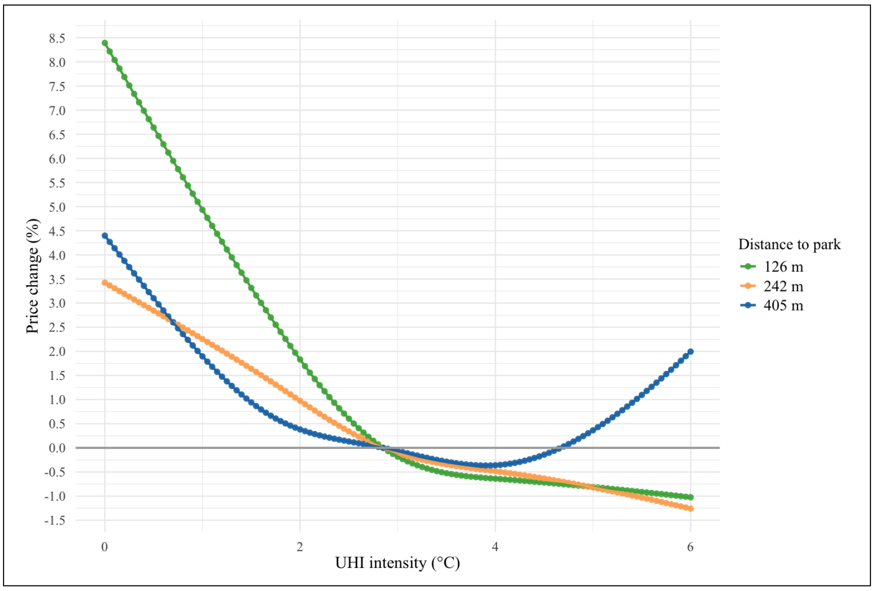
Green space is a critical cooling factor in UHI dynamics. Figure 2.7a illustrates how park proximity and nighttime UHI intensity jointly affect prices. Locations very close or moderately close to parks exhibit similar behavior. Under below-average UHI intensity (below approx. 2.3 °C), prices decline considerably. By contrast, more peripheral locations (0.41 km) remain stable or even post slight increases, suggesting that other locational factors dominate in these areas. At high UHI values (>4 °C), all groups show clear price reductions. This underscores proximity to parks as a critical determinant of nighttime cooling potential, especially in overheated urban areas. The discernible nonlinear effects point to complex trade-offs among noise, pollution, social location, urban density and the actual cooling delivered by green spaces.

Compared with nighttime effects, daytime patterns are more differentiated (Figure 2.7b). Properties adjacent to parks show steeper price declines as UHI intensity rises. In contrast, properties at intermediate or display smoother curves, with stable or slightly positive prices above roughly 4.5 °C (40.10 °F) of UHI. Overall, the market appears to value the cooling effects of parks less during the day than at night. Daytime benefits are concentrated in buildings directly bordering parks. While green spaces can moderate temperatures at the neighborhood scale, localized UHI intensity appears more strongly influenced by micro-level factors such as building materials and the spatial configuration of adjacent structures. This aligns with Chen et al. (2022), who show that Berlin´s inner-city, dominated by commercial activity, impermeable grey surfaces, including concrete and densely clustered buildings, elevate surface temperatures more than green or blue surfaces.

Figure 2.7: Price as a Function of UHI Intensities and Distance to Park



(a) 4 a.m.



(b) 1 p.m.

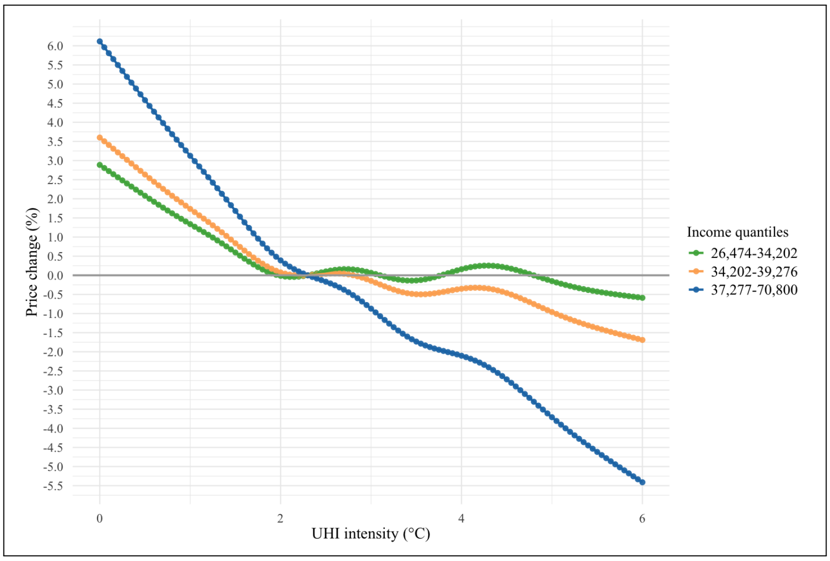
The figures illustrate the relationship between UHI intensity and estimated property price changes. Figure (a) shows results for 4 a.m., and Figure (b) for 1 p.m. Property price changes (%) are plotted against UHI intensity (°C), measured relative to the minimum observed temperature. Price effects are estimated based on Model 4, which includes an interaction term between UHI intensity and distance to the nearest park. Distances to the nearest park are grouped into quantile-based categories with thresholds at 130 m, 240 m, and 410 m for (a), and 126 m, 242 m, and 405 m for (b).

Figures 2.8a and 2.8b plot price premiums by household-income group as a function of UHI intensity. We capture these effects by extending the baseline model with an interaction term between UHI intensity and household income groups. In both figures, the highest income group (represented by the green line in the graph) shows the steepest slope. Lower-income groups have a flatter curve and thus weaker sensitivity. By comparing both times (4 a.m. and 1 p.m.), a similar pattern is observed. However, at 4 a.m., high-income households appear more sensitive to UHI exposure, as indicated by the steeper slope of the response curve and correspondingly larger effects.

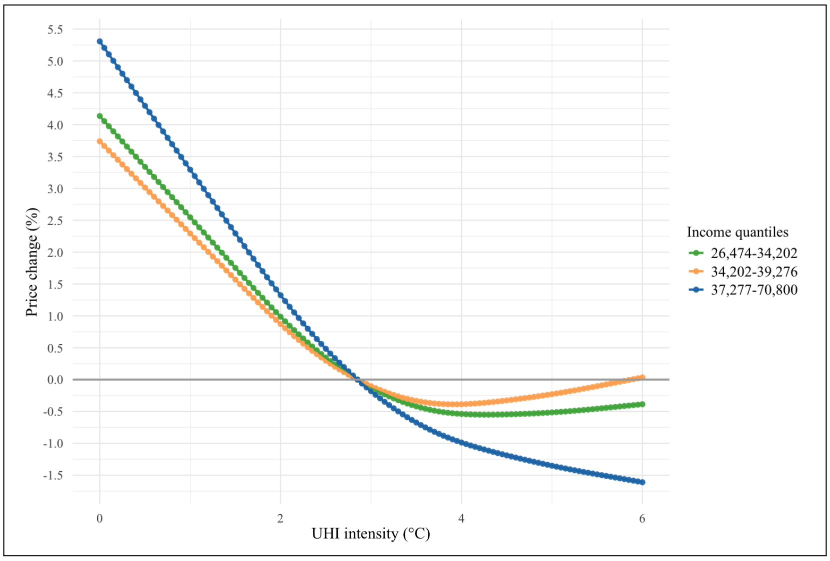
These disparities likely reflect uneven urban planning and differential access to cooling infrastructure and resources. Collectively, these patterns corroborate findings in the existing literature, a significant link between household affluence and neighborhood thermal conditions (Borsky et al., 2024; Dell et al., 2009). Higher-income households tend to have greater flexibility in residential decision-making, supported by a higher marginal willingness to pay for cooler microclimates and the financial capacity to prioritize climate-related amenities in housing choices. Consequently, affluent populations are more likely to relocate to rural, suburban or specific urban zones within Berlin with lower UHI exposure.

Overall, the findings support the notion that physical climate risks in real estate markets increasingly manifest through persistent shifts in thermal comfort. As Sinha and Cropper (2013) note, climate risks often appear as declining amenity values, especially in cities where localized heat stress becomes a structural component of housing quality. The income-heat gradient reinforces temperature as a critical, unevenly distributed determinant of amenity value, and highlights UHI effects as both a physical risk and a mechanism that can perpetuate social inequality.

Figure 2.8: Price as a Function of UHI Intensities and Household Income



(a) 4 a.m.



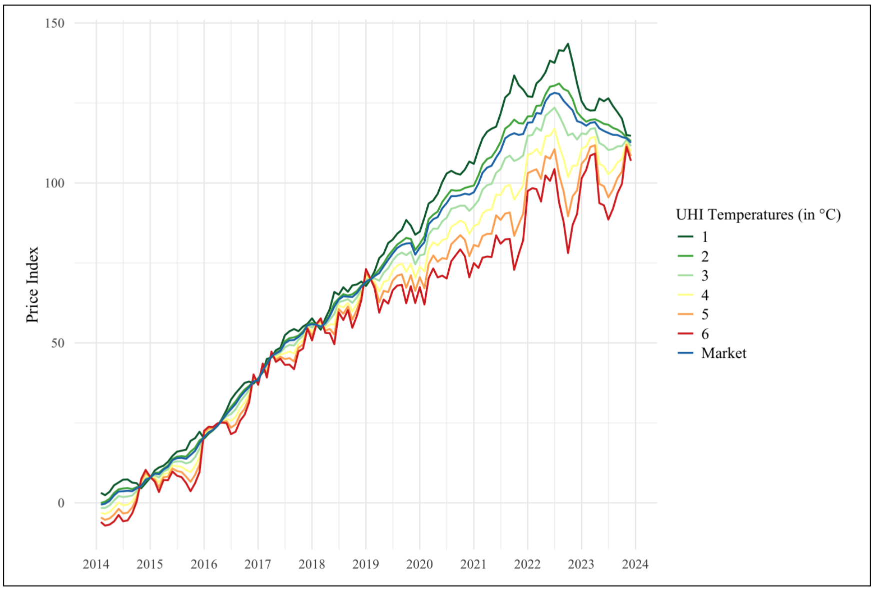
(b) 1 p.m.

The figures illustrate the relationship between UHI intensity and estimated property price changes. Panel (a) shows results for 4 a.m., and panel (b) for 1 p.m. Property price changes (%) are plotted against UHI intensity (°C), measured relative to the minimum observed temperature. Price effects are estimated based on Model 3, which includes an interaction term between UHI intensity and household income terciles. The reference point for the price effect is the average UHI intensity, expressed as the mean deviation from the minimum temperature. All values are given in degrees Celsius (°C). Household incomes are grouped into quantile-based categories, with thresholds at €26,474–34,202, €34,202–39,276, and €37,277–70,800, representing low, medium, and high-income levels.

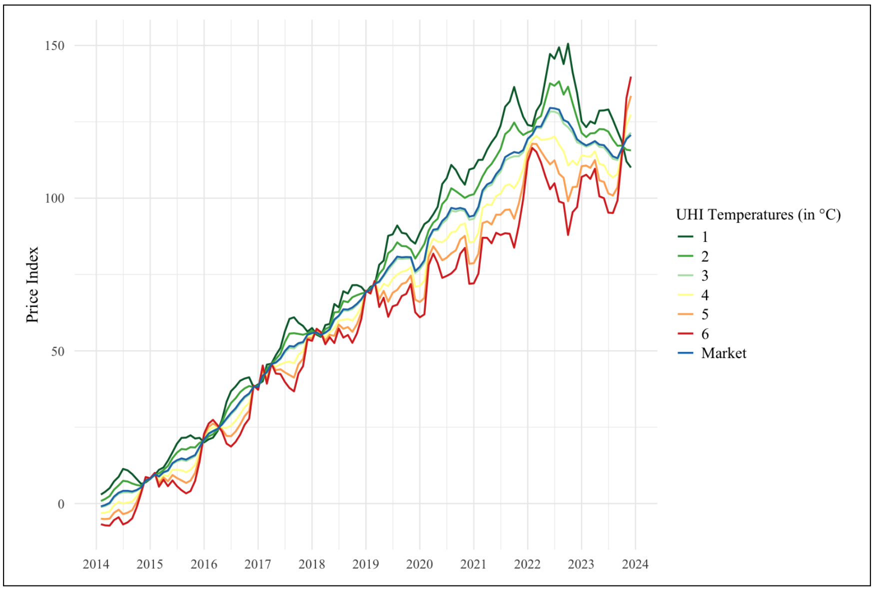
From an investor's perspective, UHI exposure is of central importance. The smoothed price trends (3-month averages) in Figures 2.9a and 2.9b show clear divergence across UHI intensity groups. In both models, which account for both heat exposure (1 p.m.) and cooling potential (4 a.m.), the coolest locations (1–3 °C UHI) consistently outperform warmer ones (4–6 °C). Over the long term, properties in cooler locations achieve more robust price growth, especially after 2020. The COVID-19 downturn is most pronounced in cooler locations, after which performance diverges further. Since 2022, amid rising rates and high inflation, the spread between UHI groups has widened. Temporal analyses reveal different dynamics. At 4 a.m. they fluctuate seasonally, spreads widen in summer and reconverge in winter, indicating higher volatility and a stronger price response to heat during warm months than in winter.

Annual price growth based on smoothed 3-month averages confirms long-term differences between cooler and warmer locations (Figure 2.10a and 2.10b). From 2014 to 2019, all temperature groups moved largely in parallel, with YoY growth between 6% and 14%. Starting in 2020, a slight divergence begin to emerge. While cooler groups (1–3 °C UHI) remain relatively steady, warmer locations (4–6 °C) lose momentum. The sharpest break occurs in 2022-2023 when all groups turn negative. However, cooler groups fare slightly better during the correction, whereas the 6 °C group remains consistently below the market average. By contrast, the daytime series (1 p.m.) shows no consistent penalty for warmer UHI locations; in some market phases, the warmest groups even outperform. Central locations with high demand, or speculative dynamics, the climatic impact might be temporarily counteracted. This suggests that heat exposure during the day is less of a risk factor than nighttime heat stress and a limited cooling potential.

Figure 2.9: Price Trends across UHI Intensities



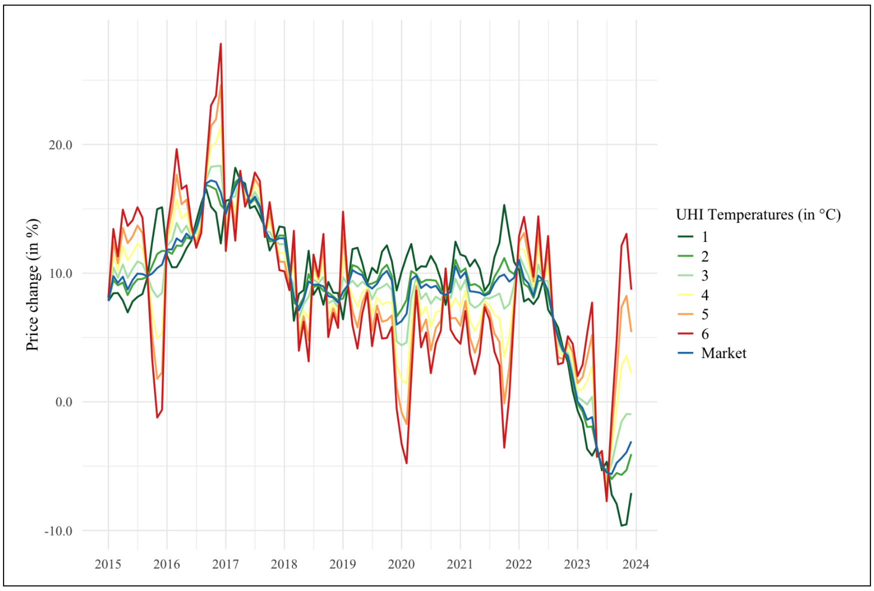
(a) 4 a.m.



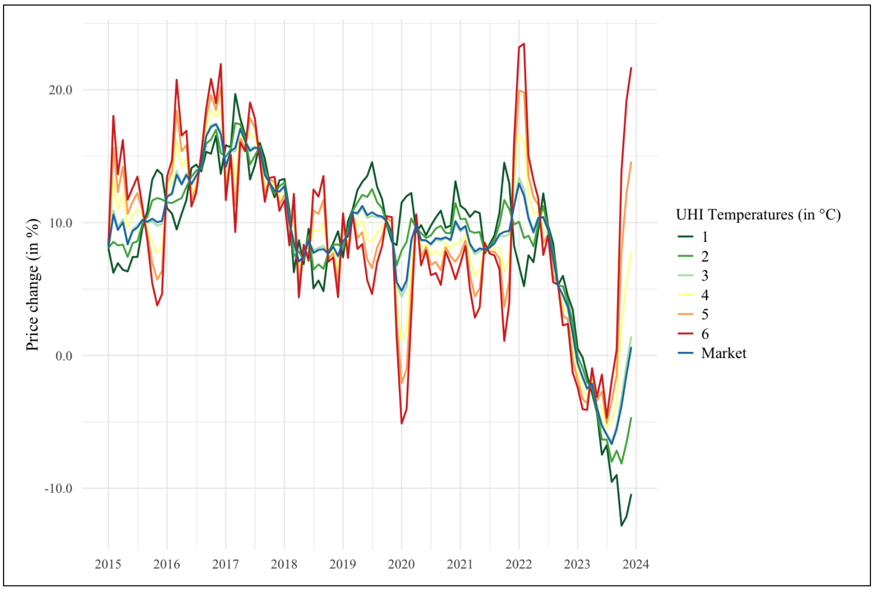
(b) 1 p.m.

The figures show the indexed long-term trend in estimated property price effects across different levels of UHI intensity. Figure (a) presents results for 4 a.m., and Figure (b) for 1 p.m. Colored lines represent distinct UHI intensity levels in degrees Celsius (°C), with a green-to-red scale from lower to higher intensities. The blue line represents the overall market average. Price effects are estimated based on Model 1, the baseline GAM without interaction terms. The index is based on January 2014 and calculated using a three-month moving average. The x-axis represents the observation period from 2014 to 2023.

Figure 2.10: Year-on-Year Price Change across UHI Intensities



(a) 4 a.m.



(b) 1 p.m.

The figures illustrate the year-on-year variation in estimated property price effects across different UHI intensity levels. Figure (a) presents results for 4 a.m., and Figure (b) for 1 p.m. Colored lines represent UHI intensity levels in degrees Celsius (°C), using a green-to-red palette from lower to higher intensities. The blue line represents the overall market average. Price effects are estimated based on Model 1, the baseline GAM without interaction terms. Year-on-year changes are computed from a three-month moving average. The x-axis represents the observation period from 2014 to 2023.

Table 2.5: House Price Growth and Risk Return Metrics by Heat Exposure and Cooling Potential

(a) 4 a.m.

UHI Intensity (°C)	**1**	**2**	**3**	**4**	**5**	**6**
Cum. Growth (%)	960.7	947.6	936.7	928.1	921.7	917.4
Av. Growth (%)	8.9	8.8	8.7	8.6	8.5	8.5
Risk Ratio (%)	5.9	5.3	5.0	5.2	5.7	6.5
Return-to-Risk Ratio	1.50	1.65	1.72	1.67	1.51	1.32
Compound Average Growth Rate (%)	6.0	5.9	5.8	5.6	5.5	5.4

(b) 1 p.m.

UHI Intensity (°C)	**1**	**2**	**3**	**4**	**5**	**6**
Cum. Growth (%)	940.85	944.24	950.20	958.75	969.90	983.68
Av. Growth (%)	8.71	8.74	8.80	8.88	8.98	9.11
Risk Ratio (%)	6.37	5.62	5.20	5.23	5.71	6.57
Return-to-Risk Ratio	1.37	1.56	1.69	1.70	1.57	1.39
Compound Average Growth Rate (%)	5.79	5.99	6.20	6.40	6.61	6.82

Tables (Table 2.5a) and (Table 2.5b) report key performance indicators (KPIs) for UHI intensity groups at 4 a.m. and 1 p.m., respectively. All values are derived from year-over-year (YoY) estimates based on Model 1; formulas appear in the Research Methodology section. The KPIs are Cumulative Growth (%), which captures total long-term price change within each UHI intensity group; Average Growth (%), mean annual YOY increase; Risk (%) volatility, measured as the standard deviation of YOY growth; Return-to-Risk Ratio provides a normalized performance metric accounting for risk exposure; and Compound Average Growth Rate (CAGR, %) expresses the smoothed annualized growth rate. Together, these KPIs provide a comprehensive performance profile across UHI groups and enable comparisons between nighttime (4:00 a.m.) and daytime (1:00 p.m.) measures.

The calculated KPIs confirm this pattern. Tables 2.5a and 2.5b show that reduced nighttime cooling (4 a.m.) serves as a price-depressing risk factor, while the heat exposure during the day (1 p.m.) tends to be viewed by the market as neutral to slightly positive. Table 2.5a indicates that, at night, properties in the cooler UHI groups (1–3 °C) outperform across all indicators. They post higher average growth, lower volatility and a more favorable return-to-risk ratio, indicating greater resilience to market cycles.

During the day, warmer locations show slightly higher risk, but this is offset by above-average cumulative and average returns (see Table 2.5b). Warmer groups (4–6 °C) in particular show a positive relationship between return and risk (e.g. 1.57 for 5 °C). Thus, in central locations with strong infrastructure, daytime heat may be perceived as less detrimental or be better mitigated by urban planning and technical measures.

2.6 Concluding Remarks

This study applies a semi-parametric framework to assess the impact of UHI effects on residential property prices in Berlin between 2014 and 2023. Using high-resolution temperature data at a 30-meter grid level, we identify average UHI intensities ranging from approximately 2.32 °C to 2.87 °C, with localized urban hotspots exceeding 6.5 °C. Above-average UHI intensity is associated with price discounts of up to 2 %, while below-average intensity corresponds to premiums of up to 4.5 %. Risk-adjusted return metrics reinforce this pattern. Nighttime cooling potential has a larger and more persistent impact on values than daytime heat exposure.

Accounting for spatial effects, we find that negative price impacts increase with distance from the CBD and are more pronounced for properties near parks, despite their localized cooling benefits, and for properties further away from the CBD, where densely sealed surfaces intensify the heat impact. By contrast, in the immediate CBD, central-location advantages outweigh heat-stress penalties.

Clear differences emerge between income groups. Price penalties for higher UHI intensities are largest in high-income segments, indicating wealthier households are more heat-averse and better able to escape or mitigate the effects of heat stress. This pattern aligns with existing evidence on climate-driven residential sorting and uneven adaptive capacity, amplifying socioeconomic inequalities as lower-income groups bear a disproportionate burden of climate risks.

Our findings suggest that market participants assess microclimatic conditions at both the building and neighborhood levels and capitalize these into property values. The inverse relationship between UHI intensity and prices indicates that markets price in tangible costs of heat-impaired building and infrastructure performance. Concurrently, deteriorating building performance under escalating heat reduces thermal comfort and degrades air quality. This erodes climate amenities and diminishes location appeal. Although UHIs differ from acute hazards such as floods or wildfires, their financial materiality is comparable.

For policymakers and city planning authorities, these findings necessitate integrating UHI resilience into urban planning measures, including the preservation of ventilation corridors and the expansion of green infrastructure, as well as mitigation and resilience efforts at the project level. This includes targeted greening of thermal hotspots and prioritizing vulnerable neighborhoods should be a central focus. For real estate decision-makers, UHI exposure is a material financial risk. Nighttime UHI, in particular, warrants explicit consideration to avoid value losses and identify climate-resilient locations. Cost-effective measures, such as reflective/high-albedo materials, cool roofs, shading, and reduced surface sealing, can mitigate UHI at modest cost while conferring competitive advantages. For future research, our results confirm the need to address the identified research gap at the intersection of real estate markets and chronic atmospheric hazards highlighted at the outset of this study.

2.7 Appendix

Formulas for KPI Analysis

Cumulative growth rate:

$$\tilde{P}_t = \frac{P_t + P_{t-1} + P_{t-2}}{3}, \quad g_t = \frac{\tilde{P}_t}{\tilde{P}_{t-12}} - 1$$

$$G_{\text{cum}} = \frac{\tilde{P}_T}{\tilde{P}_{t_0}} - 1 \tag{2.3}$$

Average annual growth:

$$\mu_g = \frac{1}{M} \sum_{t \in \mathcal{T}} g_t \tag{2.4}$$

Risk indicator:

$$\sigma_g = \sqrt{\frac{1}{M-1} \sum_{t \in \mathcal{T}} \left(g_t - \mu_g\right)^2} \tag{2.5}$$

Return-to-risk ratio:

$$R_g = \frac{\mu_g}{\sigma_g} \tag{2.6}$$

Compound annual growth rate (CAGR):

$$Y = \frac{T - t_0}{12}$$

$$\text{CAGR} = \left(\frac{\tilde{P}_T}{\tilde{P}_{t_0}}\right)^{1/Y} - 1 \tag{2.7}$$

Table 2.6: Variable Description

Variable	Source	Scale	Unit	Description
Price	A	Numeric	Euro	Price of the asset
Size	A	Numeric	sqm	Saleable floor area of the apartment
Rooms	A	Numeric	Count	Number of rooms
Age	A	Numeric	Years	Relative to year 2023. Properties built before 1900 are grouped under the construction year of 1900.
Floor	A	Numeric		Indication of the floor of the dwelling. The accessibility of apartments is assumed to be equivalent, whether on the first floor or an upper level.
Retrofitted	A	Binary	1 = yes	"Retrofitting" has taken place once the dwelling has had some improvement measures in terms of renovation or refurbishment.
Kitchen	A	Binary	1 = yes	With kitchen included
First occupancy	A	Binary	1 = yes	Newly built and first occupied
Parking	A	Binary	1 = yes	With parking included
Balcony or terrace	A	Binary	1 = yes	With a balcony and/or terrace included
Bus stop distance	B	Numeric	km	Distance to closest bus stop
School distance	B	Numeric	km	Distance to closest school
Restaurant distance	B	Numeric	km	Distance to closest restaurant
Supermarket distance	B	Numeric	km	Distance to closest supermarket
Kindergarten distance	B	Numeric	km	Distance to closest kindergarten
Playground distance	B	Numeric	km	Distance to closest playground
Park distance	B	Numeric	km	Distance to closest park
Kiosk distance	B	Numeric	km	Distance to closest kiosk
Hospital distance	B	Numeric	km	Distance to closest hospital
CBD distance	B	Numeric	km	Distance to "Alexanderplatz" as the reference point, accounting for metropolitan centrality and spatial fixed effects.
Longitude	A	Numeric		Longitude coordinate
Latitude	A	Numeric		Latitude coordinate
Population per postal code	C	Numeric		Inhabitants per postal code
Houshold income	A	Numeric	Euro	Average income per household by postal code
Month (YYYYMM)	A	Factor	60 levels	Monthly time dummies for the date of disclosure from April to September, included to assess seasonal patterns.
UHI 4am	D	Numeric	°C	Temperature deviation at 4:00 AM from Berlin's temperature minimum
UHI 1pm	D	Numeric	°C	Temperature deviation at 1:00 PM from Berlin's temperature minimum

The table presents a detailed overview of the variables used in this analysis. These include numerical measurements such as the property's list price (in euros), floor area (in square meters), and the age relative to the year 2023. Proximity to local amenities is captured through distances to the nearest bus stops, schools, and restaurants. Additional binary variables denote specific features, including kitchens, balconies or terraces, parking spaces, and elevators. Environmental exposure is measured using temperature readings recorded at 4 a.m. and 1 p.m. on the day the property was listed. A binary variable indicates whether the property has been retrofitted, capturing refurbishment or energy-efficient improvements. Population density at the postal code level is included to reflect local demographic conditions, while monthly time dummies control for seasonal and temporal variation in property listings.
Sources: A = Value market data, B = OpenStreetMap, C = GfK, D = Meteoblue.

Table 2.7: Correlations of Variables – Part 1

	Price	Log price	Size	Log size	Rooms	Age	Longitude	Latitude	School distance	Kinder-garten distance	Restaurant distance
Price	1.00										
Log price	0.92	1.00									
Size	0.75	0.73	1.00								
Log size	0.72	0.74	0.97	1.00							
Rooms	0.59	0.61	0.83	0.84	1.00						
Age	-0.12	-0.12	-0.02	-0.04	-0.07	1.00					
Longitude	-0.04	-0.02	-0.04	-0.03	-0.01	-0.11	1.00				
Latitude	0.01	0.01	-0.02	-0.02	-0.01	-0.00	0.01	1.00			
School distance	-0.05	-0.06	0.01	0.02	0.02	-0.16	-0.03	-0.11	1.00		
Kindergarten distance	-0.04	-0.06	0.01	0.02	0.02	-0.20	-0.01	-0.14	0.42	1.00	
Restaurant distance	-0.15	-0.18	-0.03	-0.01	0.02	-0.22	0.01	-0.12	0.32	0.38	1.00
Supermarket distance	-0.04	-0.05	0.02	0.03	0.03	-0.16	-0.14	-0.15	0.28	0.38	0.48
Kiosk distance	-0.12	-0.14	-0.01	0.01	0.03	-0.24	0.03	0.06	0.28	0.29	0.43
Park distance	-0.11	-0.14	-0.01	-0.00	0.02	-0.10	0.02	-0.11	0.28	0.27	0.29
Playground distance	-0.11	-0.14	-0.01	-0.00	0.02	-0.10	0.02	-0.11	0.28	0.27	0.29
CBD distance	-0.17	-0.19	-0.01	0.01	0.04	-0.14	-0.35	-0.44	0.31	0.32	0.42
Bus distance	-0.01	-0.01	-0.00	0.00	-0.00	-0.01	0.08	0.04	-0.04	0.01	0.17
Hospital distance	-0.11	-0.12	-0.05	-0.04	-0.01	-0.09	0.31	-0.09	0.13	0.08	0.16
Population per postal code	-0.06	-0.04	-0.07	-0.06	-0.05	-0.02	0.40	0.23	-0.06	-0.07	0.08
Household income	0.21	0.24	0.05	0.06	0.06	-0.13	-0.11	-0.16	0.17	0.22	0.16
Log household income	0.22	0.25	0.05	0.06	0.06	-0.13	-0.12	-0.16	0.17	0.21	0.15
Temp 4 am	0.02	0.02	-0.00	-0.01	-0.01	0.01	0.00	-0.00	-0.02	-0.01	-0.03
Temp 1 pm	0.02	0.02	-0.01	-0.01	-0.01	0.01	0.00	-0.00	-0.02	-0.01	-0.03
UHI 4 am	0.05	0.06	-0.02	-0.03	-0.03	0.12	0.06	0.08	-0.17	-0.17	-0.30
UHI 1 pm	0.02	0.03	-0.02	-0.03	-0.03	0.09	0.07	0.08	-0.13	-0.13	-0.21

Table 2.8: Correlations of Variables – Part 2

	Supermarket distance	Kiosk distance	Park distance	Playground distance	CBD distance	Bus distance	Hospital distance	Population per postal code	Household income	Log household income	Temp 4am	Temp 1pm	UHI 4am	UHI 1pm
Price														
Log price														
Size														
Log size														
Rooms														
Age														
Longitude														
Latitude														
School distance														
Kindergarten distance														
Restaurant distance														
Supermarket distance	1.00													
Kiosk distance	0.29	1.00												
Park distance	0.14	0.31	1.00											
Playground distance	0.25	0.26	0.36	1.00										
CBD distance	0.35	0.40	0.30	0.30	1.00									
Bus distance	0.10	0.06	0.01	-0.03	-0.02	1.00								
Hospital distance	0.04	0.27	0.16	0.06	0.21	0.02	1.00							
Population per postal code	-0.08	0.06	-0.04	-0.15	-0.20	0.11	0.08	1.00						
Household income	0.19	0.25	0.09	0.21	0.39	0.01	0.11	-0.12	1.00					
Log household income	0.18	0.25	0.08	0.21	0.39	0.00	0.10	-0.13	0.99	1.00				
Temp 4 am	-0.03	-0.03	-0.02	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.00	1.00			
Temp 1 pm	-0.03	-0.03	-0.01	-0.01	-0.02	-0.01	-0.00	-0.01	0.01	0.01	0.89	1.00		
UHI 4 am	-0.30	-0.25	-0.07	-0.14	-0.30	-0.08	-0.06	-0.01	-0.18	-0.18	0.51	0.56	1.00	
UHI 1 pm	-0.23	-0.18	-0.04	-0.11	-0.23	-0.05	-0.04	0.01	-0.15	-0.15	0.61	0.77	0.76	1.00

The table shows Pearson correlation coefficients for all numeric variables used in the analysis. Distances are measured in kilometers. Temperatures are recorded at 4 a.m. and 1 p.m. UHI is defined as the local temperature minus the citywide minimum at the respective time.

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3 Rooftop Solar Potential and Financial Performance of REITs

3.1 Abstract

Recent research indicates that green certification and benchmarking measures are increasingly impacting the financial performance of Real Estate Investment Trusts (REITs). While the signaling effect of sustainability efforts is well documented, there is still limited empirical evidence on how specific decarbonization levers create value for firms and investors. Using a novel dataset of U.S. REITs, we examine the relationship between rooftop solar potential and firm-level financial performance. Although we find limited evidence of impacts on market betas, abnormal returns or operating performance, there is a significant valuation effect on firm values that extends beyond REITs' underlying assets. Our results suggest that the market assigns higher valuations to REITs with greater solar potential, reflecting expected financial benefits from clean energy investments and reduced carbon-transition risks. We also show that firm values are influenced by upstream emissions through local grid dependencies, even when outside of the REITs' direct control.

Keywords: *REIT; Financial Performance; Firm Values; Rooftop Solar; Renewable Energy; Transition Risk.*

3.2 Introduction

Global financial markets have experienced significant growth in sustainable investment over the past decade. However, during periods of economic stress, management may view sustainability investments as a distraction and instead prioritize core business operations (Chacon et al., 2024). However, effective climate risk management may play a critical role in enhancing resilience to broader systematic risks (Albuquerque et al., 2019). Existing research provides strong evidence that asset prices are shaped not only by a company's environmental disclosure but also by actual carbon emissions and the uncertainty surrounding transition risks (Bolton & Kacperczyk, 2021; Choi et al., 2020; Matsumura et al., 2014; Ilhan et al., 2021; Seltzer et al., 2022; Bolton & Kacperczyk, 2023). While the scaling and timing of transition risks—such as declining investor appeal, reputational damage, regulatory pressure and carbon pricing—remain uncertain, carbon-intensive business models are especially exposed to these risks (Ilhan et al., 2021). Investor and lender sensitivity to corporate environmental performance is increasingly reflected in firm-level financial outcomes, rather than simply capturing other unobserved corporate risks (Chava, 2014; Krueger et al., 2020).

Many REIT portfolios include extensive rooftop areas well-suited for solar system installations.[1] Leveraging this infrastructure allows REITs to reduce their carbon footprint and unlock financial benefits, especially in states where electricity remains expensive and predominantly fossil-fuel-based. While solar potential varies by sector focus and available roof space, the benefits of renewable energy investments are not limited to large-scale warehouses or retail properties. Office buildings and other property types with more limited roof space can also benefit (Jurasz & Campana, 2019).

Electricity generated through rooftop solar systems can be sold back to the grid, provided directly to tenants through power purchase agreements (PPAs) or utilized in hybrid models.[2] Beyond revenue from electricity sales or renewable energy certificates (RECs), the Inflation Reduction Act (IRA) allows REITs, which are typically exempt from income tax liabilities, to monetize investment tax credits (ITCs) through transferability provisions. This enables REITs to sell credits to third parties, further

[1]See an article from National Association of Real Estate Investment Trusts (NAREIT) on April 22, 2022, at:https://www.reit.com/news/blog/market-commentary/reit-solar-opportunities-35-billion-square-feet-roof-space.

[2]For simplicity, we use 'solar systems' throughout this paper as a generic term. Technically, this includes both solar thermal (conversion of solar radiation to heat) and photovoltaic (PV) systems (conversion of solar radiation to electricity).

enhancing return on investment (ROI).[3]

Investing in rooftop solar enables REITs to lower operating expenses (OpEx) and boost net operating income (NOI), primarily through substantial energy cost savings by replacing grid electricity with on-site solar generation. For most REITs, solar investments are already more cost-effective than purchasing electricity from the grid.[4] Jurasz and Campana (2019) find that solar systems can reduce peak loads in commercial properties, further lowering energy costs. Solar systems are most beneficial in triple-net leases, where tenants directly benefit from energy cost savings, allowing landlords to charge higher effective gross rents (Reichardt, 2014).[5] Additionally, Devine and Kok (2015) document that environmentally efficient buildings benefit from higher occupancy rates, stronger tenant retention and shorter re-letting periods. These factors contribute to a more stable cash flow and lower operating costs by reducing brokerage fees and tenant incentives—ultimately driving down overall management costs for REITs. While most existing research on the impact of rooftop solar focuses on residential property values (Aydin et al., 2018; Dastrup et al., 2012; Hoen et al., 2013; Qiu et al., 2017), Leskinen et al. (2020) find that solar investments can also enhance commercial property yields. They suggest that the widening gap between rising electricity prices and slower rental growth, combined with the longer useful life of on-site energy assets, is lowering the risk premium for these properties.

Beyond direct financial benefits, rooftop solar is becoming a strategic asset for REITs to hedge against financially material transition risks. Decarbonization through on-site renewable energy generation and building electrification can make portfolios more resilient to future regulatory changes, such as disclosure mandates or carbon pricing. Premiums for solar-ready properties often reflect market expectations about future carbon costs, incorporating regulatory risks from building performance standards and carbon pricing mechanisms, such as Boston's Building Emissions Reduction and Disclosure Ordinance (BERDO) and New York City's Local Law 97 (LL97), both of

[3]The U.S. Department of the Treasury and the Internal Revenue Service (IRS) issued final regulations under the IRA of 2022 for transferable tax credits, effective July 1, 2024. See: https://www.govinfo.gov/content/pkg/FR-2024-04-30/pdf/2024-08926.pdf.

[4]See Morgan Stanley's May 6, 2022 report highlighting that for the 50 largest U.S. REITs, investing in solar energy systems is cheaper than purchasing grid electricity: https://static1.squarespace.com/static/5d1fb5921d73890001c2b867/t/6299001e3362940fc5b412ac/1654194213957 /MSNA20220325110760+%288%29.pdf.

[5]A REIT's ability to leverage its solar potential may be limited by complex ownership structures (e.g., shared rights or covenants) or restrictive tenant agreements—even under triple-net leases—due to consent requirements, access limitations, or difficulties allocating financial benefits.

which, starting in 2024, impose annual greenhouse gas (GHG) emissions limits and fines for non-compliance on commercial properties. Concurrently, pressure from global disclosure regimes is intensifying. While mandatory reporting under the U.S. Securities and Exchange Commission (SEC)'s climate rules remains uncertain, REITs still face intense capital market pressure to align voluntary disclosures with the International Sustainability Standards Board (ISSB). REIT management has also placed increasing public emphasis on on-site renewable energy generation.[6] It is therefore reasonable to assume that sophisticated investors recognize the financial benefits of clean energy investments.[7]

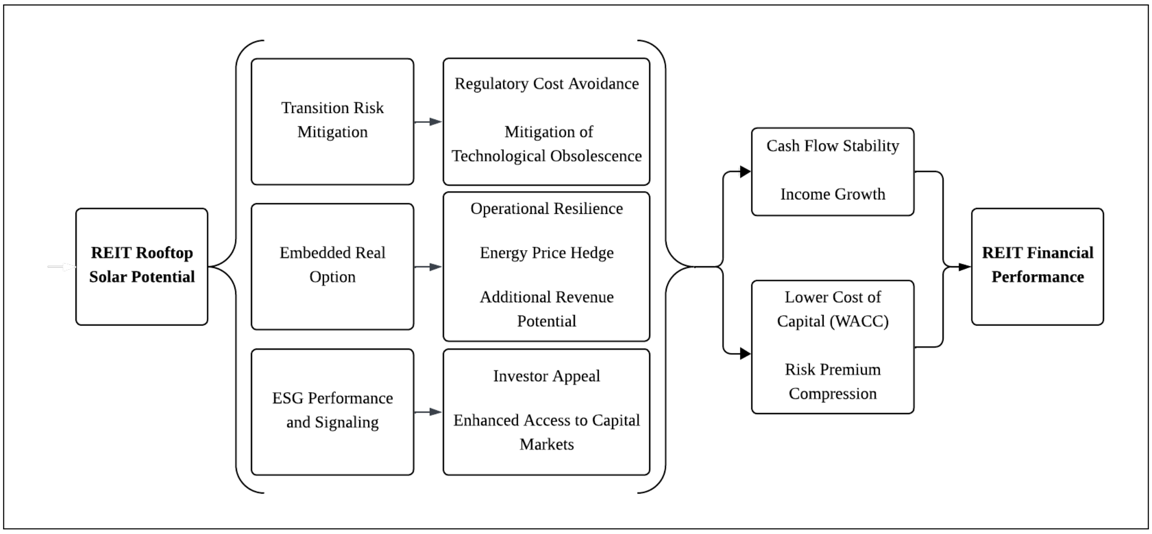
To accurately assess the firm-level impact of solar strategies, it is essential to determine whether asset-level premiums translate into REITs' capital market valuations. These investments are only expected to affect valuations and stock prices if there is a connection between asset-level value creation and REIT-level valuation. Findings by Ling et al. (2020) and Lee et al. (2022) support the existence of substantial and consistent green premiums across markets. These findings suggest that the potential to mitigate transition risk at the asset level—for example, through rooftop solar systems—can be capitalized even without immediate implementation, especially given environmental, social, and governance (ESG)-driven capital allocation trends. In this sense, the solar potential of REIT portfolios can be understood as an extension of the well-established green building premium. This concept is gaining importance as the industry shifts from certification orientation to measurable environmental performance and transition risk reduction. Figure 3.1 presents a theoretical model identifying critical pillars through which rooftop solar potential may influence firm-level financial outcomes.

Although limited empirical evidence supports the property-level benefits of solar in commercial real estate, to our knowledge, the relationship between rooftop solar and REIT financial performance remains unexplored. Existing REIT literature primarily focuses on third-party green certifications, often used by firms to signal environmental commitment and help investors satisfy sustainability mandates. Beyond the clientele effect, there is limited understanding of how actual transition risks are priced into valuations or how upstream emissions affect REIT financial performance. This paper

[6] NAREIT's REIT Industry Sustainability Report 2024 notes that by the end of 2023, 78% of REITs reported on on-site clean energy initiatives (including all forms of on-site renewable generation).

[7] See Morgan Stanley's May 6, 2022, report detailing its methodology for incorporating REITs' rooftop solar potential into stock price forecasts: https://static1.squarespace.com/static/5d1fb5921d73890001c2b867/t/6299001e3362940fc5b412ac/1654194213957 /MSNA20220325110760+%288%29.pdf.

Figure 3.1: Conceptual Framework linking Rooftop Solar Potential to REIT Financial Performance



The figure illustrates a conceptual framework outlining the key mechanisms through which rooftop solar potential can affect REITs by linking sustainability drivers to firm-level financial performance.

addresses that gap by using a unique dataset to examine the impact of rooftop solar potential and carbon offset factors on stock performance, operating performance and firm values.

To pursue our analysis, we compile financial data and firm characteristics from listed U.S. equity REITs and match these with newly available data on rooftop areas suitable for solar installations across each REIT's property portfolio. We also factor in the carbon intensity of the local electric grids serving these properties. This dual approach serves as a proxy for both the potential to mitigate transition risks—by switching from grid electricity to renewable energy—and exposure to upstream emissions. We aggregate the property-level data sets for each REIT in our panel to quantify the company-level financial impact. To validate our methodology and ensure accurate empirical results, we perform a series of robustness checks. REITs provide a suitable framework for identifying potential contemporaneous effects on financial results, as profitability ratios and stock returns can be tracked periodically. Moreover, REITs' underlying properties are actively traded in secondary markets, enabling direct comparison between asset values and shareholder value—offering valuable insights into market expectations.

Our results indicate no significant relationship between REITs' solar potential and stock performance, and only limited evidence of an effect on operating performance. Given the barriers REITs have been facing in adopting rooftop solar, we attribute this primarily to the lack of widespread implementation across the industry. However, we find strong statistical and economic evidence that both solar potential and carbon offset potential significantly affect firm values. This suggests that markets are already incorporating the financial benefits and reduced risks associated with clean energy into REITs' expected future cash flows.

Furthermore, we find that firm values are influenced not only by direct carbon emissions but also by upstream emissions tied to local grid dependencies. Overall, these results have important implications for REIT management, stakeholders and policymakers. They extend the existing literature by providing a new perspective on environmentally sustainable property investment, clarifying how transition risks are priced and demonstrating how property portfolios can be actively leveraged to reduce those risks while generating financial value.

The remainder of the paper is structured as follows. The next section reviews the related literature. We then present our data sources, variables and summary statistics, followed by a description of our research methodologies. The subsequent section presents our results and robustness checks. The last section provides our conclusions.

3.3 Related Literature

In line with broader financial literature, research on REITs confirms that transition risks influence investor capital allocation and directly impact asset prices. Salisu et al. (2024) provide evidence that such risks substantially affect both global and regional REIT markets, underscoring the importance of integrating climate-related risk considerations into investment decisions. Given the limited availability of comprehensive whole-building energy data and corresponding emissions data, existing studies focus on two primary metrics to elucidate the financial impact of green practices at the firm level: (1) either examining the proportion of environmentally certified properties within REIT portfolios or (2) assessing GRESB scores and disclosure. Eichholtz et al. (2012) and Fuerst (2015) show that both the share of LEED- and Energy Star-certified properties and the GRESB score have a positive impact on REITs' operating performance and systematic risk, suggesting reduced exposure to energy price fluctuations and regulatory risks. There is also evidence that greener REITs are associated with superior stock performance, as highlighted by Eichholtz et al. (2012) and Sah et al. (2013).

Moreover, REITs that engage in environmental-sustainable practices benefit from lower debt financing costs. This is evident at both the property and the firm level (Eichholtz, Holtermans, & Kok, 2019; Feng & Wu, 2023). While finding evidence supporting a reduced cost of capital for greener REITs, Devine et al. (2024) also show that green bond issuance improves corporate environmental performance as well. By isolating the income and capital channels that drive the positive impact of green property investment at the firm level, Devine and Yönder (2023) examine the underlying pricing mechanisms of green building investments of REITs identified in previous studies. Beyond the benefits of better operating performance, lower borrowing costs, and reduced systematic risk at the property level, their research highlights that the relative premium in equity markets exceeds the premium observed in property markets. They find that the mere participation of REITs in such certification schemes has an impact on investor and lender pricing, confirming the signaling effects of certifications found by Bond and Devine (2016).[8]

While the benefits to REITs of holding a higher fraction of properties with green building certifications or ratings are well documented in the literature, it is critical to recognize that these frameworks alone, in their current form, are not sufficient to optimize both environmental and financial performance (Clayton et al., 2021; Newsham et al., 2009). Using GRESB performance scores for REITs, Chacon et al. (2024) provide evidence that capital of REITs might be overallocated to ESG investments, resulting in lower firm values and cash flow. Although all three dimensions of ESG are taken into account, the study indicates that a careful balance should be struck between the short-term costs and long-term benefits of environmental-sustainable investments. This underscores that adherence to the box-ticking approach prevalent in certification and rating systems may not always be in the best interests of investors, lenders, and tenants in terms of capital allocation and thus also of efficient transition risk management. Although the underlying certification and rating systems are not perfect, they can serve as strategic differentiators and influence capital flows, as existing studies evidence. A meta-analysis by Zheng and Lee (2025) suggests that ESG mandates increasingly influence institutional capital allocation within the real estate sector. Thus, they may act as a leading indicator of actual environmental performance before concrete property-level measures are implemented.

[8] There is also an extensive body of literature highlighting the benefits of environmentally sustainable investments at property level. See An and Pivo (2020); Chegut et al. (2014); Devine et al. (2022); Eichholtz et al. (2010, 2013); Fuerst and McAllister (2011); Holtermans and Kok (2019); Reichardt et al. (2012); Szumilo and Fuerst (2015); Wang et al. (2025); Wiley et al. (2010).

Nevertheless, focusing on actual carbon and energy intensity is essential to effectively managing transition risks in property portfolios, as suggested by findings of Akhtyrska and Fuerst (2024). In this context, operational energy plays a key role not only from an environmental perspective, but also from an economic one. This importance, particularly for electricity, is expected to grow in the coming years. First, the phase-out of on-site fossil fuel combustion is driving a shift toward electrification of heating systems. Second, electric cooling loads, already a significant component of today's commercial building energy use, are expected to increase, particularly during periods of extreme heat. Third, geopolitical tensions combined with uncertainty about carbon pricing are expected to put additional inflationary pressure on electricity prices (Fuss et al., 2009). Despite being historically the largest portion of a commercial property's OpEx, energy costs are proving to be a highly manageable factor (Wiley et al., 2010).

Krueger et al. (2020) note, that institutional and long-term investors in particular are prioritizing resilience against transition risk over divesting from assets with heightened risk exposure. REITs that focus on long-term value creation are likely to benefit from a performance premium compared to their peers (Feng et al., 2022). In addition to adopting energy efficiency measures, investments in on-site renewable energy can significantly reduce the transition risk of real estate portfolios, particularly as carbon pricing schemes become more widespread. This is because REITs are becoming less dependent on the decarbonization of the local grid and on-site renewable energy enables a more efficient switch to electrified heating and cooling systems. According to Lee and Liang (2024), carbon-transition risks, such as emissions trading schemes, are not only raising investor awareness of risk management and the financial viability of listed real estate investments, but are also driving firms to realign their priorities and strategies. They find evidence that firms in regions affected by these policies are better positioned to meet evolving environmental standards in real estate markets through the integration of innovation and technology.

3.4 Data and Summary Statistics

We collect data on firm characteristics of all available U.S. listed equity REITs from 2012 to 2023 at an annual frequency, sourced from S&P Capital IQ Pro (formerly SNL Financial). Daily stock market returns are obtained from Refinitiv Datastream (formerly Reuters). Research factors and risk-free rate data are downloaded from Kenneth R.

French's Data Library.[9] Our time series data covers a full market cycle and captures potential shifts in REITs' adoption of solar systems. To account for potential selection bias, we consider all REITs regardless of property type and geographic focus.

In our analysis of the impact of REITs' solar potential on financial performance, we calculate annualized alphas and betas based on daily stock returns, using a standard 4-factor model according to Fama and French (1993) and Carhart (1997), return on assets (ROA), return on equity (ROE), market-to-book (M/B) ratio, price-to-net asset value (P/NAV) ratio.[10]

Consistent with previous studies, we include the following explanatory variables: real estate investment growth, measured as the growth rate of REITs' real estate investments based on the previous reporting period; total assets, defined as total assets owned by the REIT and reported on the balance sheet; debt-to-equity (D/E) ratio, defined as debt as a percentage of total equity; firm age, calculated as one plus years since initial public offering (IPO) or establishment of REIT status; and percentage held by institutional owners, which might add explanatory power with regard to adoption of sustainability practices, as suggested by Dyck et al. (2019) and Krueger et al. (2020). In line with Devine and Yönder (2023), we calculate the proportion of properties that are less than 10 years old. This allows us to control for the quality of property portfolios and the potential suitability of the buildings for the installation of solar systems. Real gross domestic product (GDP) growth by MSA, considered a typical leading indicator of real estate returns, is included as an external variable to account for potential omitted economic drivers.[11] Following Capozza and Seguin (1999), we use the Herfindahl–Hirschman Index (HHI) to measure both the geographic and property type diversification of the REITs in our sample, where s_i denotes a REIT's market concentration, either in terms of its portfolio share by MSA or real estate property type. Index values range from zero to one, with values close to zero suggesting high diversification. The HHI may capture both the heterogeneity of solar potential across property types and local environmental awareness, such as mandatory solar requirements for properties.

$$HHI = \sum_{i=1}^{N} s_i^2 \tag{3.1}$$

[9]See Kenneth R. French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data-library.html.

[10]A more detailed description of our dependent variables and the estimation strategy we employ can be found in the next section of this paper.

[11]See e.g., Case et al. (2000); Feng and Wu (2022); Lieser and Groh (2014); Quan and Titman (1997).

To determine the rooftop solar potential of REITs, we first derive latitude and longitude data from the property addresses of all REIT-owned properties by applying geographic information system (GIS) methods. We then use Google's Solar application programming interface (API) to match the latitude, longitude and building size data with the roof area data. The Solar API applies machine learning to assess the available roof area for solar arrays on properties based on satellite images, shading analysis, roof elevations, building outlines, and built-up roof areas. In particular, it identifies potential obstacles on the roof, such as ventilation systems, that could prevent the installation of solar panels.[12] By focusing on the specific characteristics of individual properties, our dataset provides a more accurate determination of solar potential than generalized assumptions based on building footprint or total roof area of buildings. We define a REIT's solar potential as the average maximum solar array area (in square feet) that can be installed on the roof of a property n owned by a REIT i in year t. By weighting each property's maximum solar array area relative to the REIT's total area, we account for differences in portfolio size and property type focus.

To further address the impact of solar installations on operational carbon emissions and to proxy the potential to mitigate transition risks by switching from grid electricity to solar, we include a REIT-specific carbon offset factor. This factor measures the equivalent carbon emissions in kilograms of CO_2 per megawatt-hour (MWh) of grid electricity that a solar system would displace, reflecting each REIT's unique carbon displacement potential. To determine the REIT-specific factors, each property in our sample is matched to the carbon intensity of its respective e-grid. Since grid electricity consumption—and therefore carbon emissions—is directly proportional to property size, the carbon offset factor for each REIT is again calculated by weighting the property-specific offset factor by its square footage relative to the REIT's total floor area. We consider this variable to have additional explanatory power with respect to solar potential, as the results of Bolton and Kacperczyk (2023) show that the financial performance of firms is also affected by indirect upstream emissions. For REITs, this suggests that not only the environmental performance of properties, but also the energy mix of the electrical grid is a critical factor influencing transition risk exposure.[13]

[12]See the detailed documentation of the Solar API on the Google Maps Platform: https://developers.google.com/maps/documentation/solar. We used a randomized subsample to compare the estimates with the footprint data from OpenStreetMap. In line with existing literature, we found that on average 60% of the footprint of commercial properties is available for PV installations.

[13]Due to multicollinearity between carbon offset factors and local utility rates, we do not include the latter in our dataset.

$$Solar\ Potential_{i,t} = \sum_{n=1}^{N} \frac{Floor\ Area_{i,t}^{n} \times Max\ Array\ Area_{i,t}^{n}}{Floor\ Area_{i,t}} \tag{3.2}$$

$$Carbon\ Offset_{i,t} = \sum_{n=1}^{N} \frac{Floor\ Area_{i,t}^{n} \times Max\ Carbon\ Offset_{i,t}^{n}}{Floor\ Area_{i,t}} \tag{3.3}$$

REITs with incomplete data on the latitude and longitude of their properties or other missing control variables are excluded from our analysis. Moreover, we only consider firms for which we can obtain at least 90% of the solar potential data across the entire portfolio via Google's Solar API. Our final sample consists of 103 REITs with a balanced distribution of property types and geographic focus. To reduce the influence of outliers, we apply winsorization to the variables at the 5th and 95th percentiles. The summary statistics are presented in Table 3.1.

Table 3.1: Descriptive Statistics

Statistic	Mean	Median	St. Dev.	Min	Max
Alpha (%)	0.37	0.90	6.78	−13.29	13.93
Beta	0.77	0.74	0.28	0.00	2.66
ROA (%)	1.95	1.97	1.34	−0.90	4.93
ROE (%)	4.75	3.98	8.75	−13.00	24.64
M/B ratio	2.29	1.89	1.49	0.78	6.83
P/NAV ratio	0.91	0.93	0.11	0.67	1.17
Solar potential (sq ft)	37,889.33	29,235.59	29,819.40	3,911.27	130,619.10
Carbon offset (kgCO_2/MWh)	556.00	545.24	64.85	391.20	660.76
Total assets ($B)	5.11	3.22	5.18	0.08	19.60
Real estate inv. growth (%)	7.55	3.88	17.37	−10.67	71.21
D/E ratio	1.38	1.04	0.97	0.38	4.06
Institutional ownership (%)	14.60	14.93	3.20	3.57	19.14
Share buildings < 10 years (%)	11.49	8.49	8.16	1.38	32.68
Firm age	18.58	19.00	9.52	2.00	44.00
HHI property type	0.80	0.90	0.21	0.28	1.00
HHI region	0.19	0.08	0.21	0.02	0.73
GDP growth (%)	2.43	2.11	0.77	0.43	4.14

The table presents the descriptive statistics for the variables used in this analysis covering the sample period from 2012 to 2023. Firm characteristics are sourced from S&P Capital IQ Pro. Annualized alphas and betas are calculated using a standard Fama-French-Carhart 4-factor model. The key independent variables, solar potential and carbon offset, are obtained from the Google Solar API. To mitigate the influence of outliers, the variables are winsorized at the 5th and 95th percentiles.

The average estimated market beta is 0.76, while the average annualized alpha is 0.4%.

REITs have an average ROA of 1.95% and a ROE of 4.75%. The mean M/B ratio is 2.29 and the mean P/NAV ratio is 0.91. REITs hold on average $5.11 billion in real estate assets, with an average D/E ratio of 1.38. REITs' real estate investments are growing at an average annual rate of 7.55%. The mean firm age is 18.58 years, with 11.00% of properties less than 10 years old. With an average HHI of 0.19 across regions compared to 0.80 for property types, REITs exhibit greater geographic diversification than sector diversification. Institutional owners hold on average 14.60% of REIT shares. For an average REIT portfolio in the sample, the mean solar panel array area per property is 37,889.33 square feet, with a standard deviation of 29,235.59 square feet. By using solar power instead of grid electricity, REITs could offset an average of 556.00 kilograms of carbon per MWh of solar energy generated, with a standard deviation of 64.85 kilograms of carbon per MWh. This suggests that, although there is some variation in the solar potential of REITs, their ability to displace carbon remains relatively consistent across our sample, especially when compared to the significant regional differences in U.S. eGRID emission factors.[14]

3.5 Research Methodologies

We first estimate the impact of solar potential and carbon offset factors on REIT stock performance by calculating alphas (abnormal return) and market betas (systematic risk) for each REIT in our sample using a standard 4-factor model according to Fama and French (1993) and Carhart (1997).[15]

$$\left(R_{i,t} - R_{f,t}\right) = \alpha_i + \beta_i \left(R_m - R_f\right)_t + \gamma_{i1} SMB_t + \gamma_{i2} HML_t + \gamma_{i3} MOM_t + \varepsilon_{it} \tag{3.4}$$

$R_{i,t}$ is the daily stock return of REIT i on day t. SMB (small minus big), HML (high minus low) and MOM (momentum) are the Fama-French-Carhart factors. While some studies include the S&P 500 index as a proxy for market return R_m, we follow the large body of existing REIT literature by using the NAREIT index in our analysis.[16] Abnormal returns may reflect a positive market perception of REITs' solar potential and the associated financial benefits beyond the stock price. As suggested by Eichholtz et al. (2012), betas may provide valuable insights into REITs' exposure to systematic

[14] See U.S. Environmental Protection Agency (EPA)'s GHG Emission Factors Hub for regional default emission factors: https://www.epa.gov/climateleadership/ghg-emission-factors-hub.

[15] For additional robustness, we also run the estimation using a Fama and French (2015) five-factor model. The results show consistent values for alphas and betas.

[16] We derive annual alphas by assuming that a year has 252 trading days.

risk factors, such as fluctuating energy prices or environmental policies, which could potentially be mitigated by solar.

Next, we examine the impact of our key independent variables on REITs' operating performance. We calculate ROA and ROE by dividing net income (NI) by lagged total assets and total equity, respectively. Although funds from operations (FFO) is often considered a more direct measure of cash flows from core business operations, we use NI for three methodological reasons. First, this approach aligns with the existing financial literature and previous REIT sustainability studies.[17] Second, NI captures the specific financial effects of solar investments, such as tax benefits, depreciation, and financing costs, which FFO may obscure. Third, using both ROA and ROE leverages their complementary analytical strengths. While ROA is less influenced by leverage and provides a measure of asset-level efficiency (Core et al., 2006), ROE is generally regarded as the superior metric for evaluating operating performance from the shareholder's perspective, capturing how effectively equity capital is employed (Brown & Caylor, 2009). Particularly for REITs that are already leveraging their solar potential, the aforementioned cash flow effects as well as reduced operating and management expenses may be reflected in both ROA and ROE.

Finally, we estimate the impact of *Solar Potential* and *Carbon Offset* on corporate valuation. For this purpose, we calculate the M/B ratio which is defined as a REIT's equity market capitalization as a multiple of its book value. Market capitalization incorporates the fair price of a stock, determined in standard valuation models as the present value of firm's future dividends or earnings. Thus, according to Fama and French (1995), the price of a stock and therefore our dependent variables may be affected by both growth rates of future cash flows and changes in investors' required rate of return. Boudry et al. (2010) note that REITs face a double cost of equity capital, which may affect REIT values not only through public markets, but also through private markets given the active secondary market trading of REITs' underlying properties. Since the book value as a past oriented accounting measure is potentially distorted by depreciation and may not fully reflect private market influences, we also use P/NAV as an independent variable, which is calculated by dividing a REIT's share price by its net asset value relative to shares outstanding.

In our model selection, we face methodological challenges similar to those highlighted

[17] Eichholtz et al. (2012) employ both ROA and ROE as primary metrics to evaluate the impact of portfolio greenness on REIT operating performance. Their robustness check using FFO confirms the methodological soundness and consistency of NI-based measures in capturing performance effects.

by Bauer et al. (2010). Our main predictor variables—*Solar Potential* and *Carbon Offset*—vary across REITs, but are relatively constant over time. This data structure poses a challenge when using a firm fixed effects model, as it becomes difficult to disentangle the firm effects captured by our explanatory variables from those captured by the firm fixed effects, leading to multicollinearity issues. We therefore use an OLS model with sector fixed effects and heteroscedasticity-robust standard errors that are adjusted for dependencies within the firm clusters. This approach is preferable to a generalized least squares (GLS) model because, although it also accounts for auto- and cross-sectional correlation, it tends to produce overly confident standard errors, especially for large N and small T samples (Beck & Katz, 1995). Our regression model can be written as

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \gamma Z_{i,t} + \delta_{s,t} + \epsilon_{i,t} \tag{3.5}$$

where Y_{it} represents our outcome variables alpha, beta, ROA, ROE, M/B ratio, or P/NAV ratio for REIT i in year t. We use the logarithmic form of our dependent variable where the data distribution allows. X_{it} is a vector of our logarithmized independent variables of interest $Solar\ Potential_{i,t}$ and $Carbon\ Offset_{i,t}$. Z_{it} is a vector of controls and $\delta_{s,t}$ represents the sector fixed effects. We include total assets and REIT age in their logarithm. In line with prior studies, we include one-year lagged values of real estate investment growth, debt-to-equity ratio, and ROA as covariates. In line with prior studies, we include one-year lagged values of real estate investment growth, the debt-to-equity ratio, and ROA as covariates. The one-year lag length is supported by Beracha et al. (2019), who note that cash flows and expenditures are strongly linked to the property stock held by a REIT at the start of the reporting period. Since potential investment effects typically materialize only after changes in a REIT's portfolio composition and capital structure toward the end of the period, year-end financial performance is more likely to reflect the characteristics present at the beginning of that period.

To account for cross-sectional residual dependence and a potential unobserved time effect, we also estimate yearly regressions as suggested by Fama and MacBeth (1973). In these situations, the Fama-MacBeth (FM) approach provides unbiased standard errors and correctly sized confidence intervals (Petersen, 2008). Comparing the FM standard errors with the standard errors clustered at the firm level allows us to assess the relative magnitude of the firm and time effects in our models and thus a potential bias in our results. In the first step, we run T cross-sectional regressions for each year in the same setup as our panel models, where β_{0i} and β_{1i} are entity-specific intercepts and coefficients as presented in Eq. (6). From these regressions, we then derive the time series average and the variance of the aggregated coefficients to compute p-values using Fama-MacBeth standard errors.

$$Y_{i,t} = \beta_{0,i} + \beta_{1,i} X_{i,t} + \gamma Z_{i,t} + \epsilon_{i,t} \tag{3.6}$$

3.6 Empirical Results

3.6.1 Stock Performance

Table 3.2 shows the regression results for REITs' stock performance and systematic risk as measured by their alphas and betas. Columns (1) and (3) report the coefficient estimates from the Fama-MacBeth regressions, while Columns (2) and (4) provide the coefficient estimates from the fixed effects models. Although we find a positive coefficient of 0.133 for *Solar Potential* on alphas in the FM model, suggesting that REITs with more available solar array area may generate excess returns, we do not observe statistical significance in the estimated coefficients for either model. Our results therefore imply that *Solar Potential* has no explanatory power for the excess returns of REITs. Moreover, the models estimate a negative coefficient for *Carbon Offset* (Columns 1 and 2). While a negative coefficient may suggest that REITs with higher exposure to properties operating in areas with carbon-intensive grids have lower excess returns, we again find no significant results. However, if we consider REITs' solar potential as a driver of stock performance, the lack of statistical significance for alphas may indicate that potentially higher cash flows or growth rates are already priced into stock prices and therefore no excess returns are observed (Eichholtz et al., 2012).

According to Columns (3) and (4), we find no significant influence of our primary independent variable, *Solar Potential*, on market betas in either model. This implies that the systematic risk is not affected by a REIT's available solar array area. Bolton and Kacperczyk (2021) point out that the adoption of renewable energy technologies is limited to certain sectors and therefore may not be reflected in the systematic risk. We further suggest that our findings may be due to a lack of progress in solar installations.[18] While the financial viability of these strategies is contingent on a multitude of variables, including the specifics of the individual properties, the ownership struc-

[18] Although an accurate adoption rate for solar systems in REIT-held properties is unavailable, a 2022 Morgan Stanley report measured Prologis's adoption rate at around 3%. This aligns with a 2020 Wood Mackenzie report, which found an overall adoption rate of 3.5% for commercial properties in the U.S.

ture (owner-operator or third-party ownership), local utility rates, and net metering regulations, the potential economic benefits remain unrealized in many cases. Fleten et al. (2007) and Leskinen et al. (2020) note that the adoption of solar systems lags behind the pace suggested by their financial benefits. They point out that investors are delaying their investments longer than profitability analyses recommend, highlighting a discrepancy between expected and actual investment behavior. We attribute this lack of adoption to the following key barriers: First, due to their income tax exemption, REITs have historically faced challenges in using tax credits to offset taxable income or monetizing the tax credits through sale. Although recent regulations address this issue, REITs' rooftop solar systems have primarily been operated by third-party owners or through taxable REIT subsidiaries. Particularly in the case of third-party operated models, where REITs receive only a roof rent rather than the full PPA revenues, this model may be unattractive to REITs given the restrictions imposed by the roof rights granted to the operator. Second, this special tax status restricts REITs from directly taking advantage of accelerated depreciation for their renewable energy investments. Although accelerated depreciation can increase distributions to investors and thus improve overall returns, this benefit is limited to certain investors, many of which do not pay taxes on dividend income. Third, REITs with large solar potential face the challenge of generating more energy than their properties consume. However, in certain U.S. grid regions, legal and technical barriers prevent the sale of excess power back to the grid. Although community solar is available in some form in most states, rooftop community solar implemented through net metering or tax credits is included in the legislation of only a few states. In addition to the benefits for REITs, the expansion of rooftop community solar could allow households, companies, and other groups to benefit from greener, more stable, and affordable electricity rates without having to install their own solar systems.[19]

In a similar manner to *Solar Potential*, we do not find a significant relationship between *Carbon Offset* and market betas in the fixed effects model as shown in Column (4). REITs with high offset factors are more dependent on grids that have a carbon-intensive energy mix, primarily due to electricity generation from fossil fuels such as coal, oil or gas. The grid dependency and associated upstream emissions expose REITs to greater carbon risk, as evidenced by the findings of Bolton and Kacperczyk (2023). However, due to relatively stable natural gas prices and historically low carbon prices, any significant impact on REITs' sensitivity to systematic risk has likely been mitigated

[19]For additional information on community solar and data on state-specific policies, please see the NREL website: https://www.nrel.gov/state-local-tribal/community-solar.html.

to date. In addition, the lack of statistical significance is not entirely unexpected, as estimating the impact on alphas and betas derived from daily stock returns using explanatory variables based on annual data can be challenging. Furthermore, alphas and betas are themselves estimates that serve as independent variables. This adds to the complexity of deriving significant estimates for the coefficients, which is evident when compared to the overall statistical significance of our explanatory variables and covariates in other models reported in Tables 3.3 and 3.4.

Table 3.2: Regression Results for Stock Performance

Variables	Alpha		Beta (log)	
	(1)	(2)	(3)	(4)
Solar potential (log)	0.133	−0.043	0.028	−0.001
	(0.378)	(0.074)	(0.020)	(0.017)
Carbon offset (log)	−3.177	−0.641	0.135	0.334
	(2.024)	(2.256)	(0.161)	(0.339)
Total assets (log)	−0.758**	−0.572***	0.046	0.049***
	(0.348)	(0.076)	(0.029)	(0.005)
Firm age (log)	0.560	0.321*	−0.042	0.008
	(0.432)	(0.180)	(0.036)	(0.022)
Real estate inv. growth$_{t-1}$	0.049**	0.023***	−0.002***	−0.001
	(0.022)	(0.008)	(0.001)	(0.001)
D/E ratio$_{t-1}$	0.437**	0.093	0.012	0.012
	(0.219)	(0.164)	(0.013)	(0.015)
ROA$_{t-1}$	0.331	0.165**	−0.007	−0.004
	(0.283)	(0.080)	(0.016)	(0.009)
Share buildings < 10 years	−0.013	−0.027*	−0.001	−0.003
	(0.026)	(0.015)	(0.002)	(0.002)
GDP growth (MSA)	0.474	0.189	−0.020	−0.027
	(0.441)	(0.212)	(0.042)	(0.035)
Institutional ownership	0.048	0.049	0.018***	0.020***
	(0.085)	(0.056)	(0.006)	(0.007)
HHI region	−3.000	−0.899***	0.220**	0.214
	(2.044)	(0.281)	(0.089)	(0.202)
HHI property type	1.617	1.957***	0.261***	0.112
	(1.289)	(0.161)	(0.081)	(0.112)
Constant	25.157*	5.204	−2.419**	−3.627
	(13.125)	(13.381)	(1.044)	(2.218)
Coefficient estimates	FM	OLS	FM	OLS
Standard errors	FM	CL - F	FM	CL - F
Sector FE	N	Y	N	Y
Year FE	N	Y	N	Y
Observations	1,010	1,010	1,010	1,010
R-squared	0.321	0.238	0.254	0.228

The table reports the results of OLS and Fama-MacBeth regressions for the stock performance of U.S. equity REITs as a function of their solar potential and carbon offset and a vector of control variables. Annualized alphas and betas are derived from a standard Fama-French-Carhart 4-factor model. OLS regressions include both sector and year fixed effects. Heteroskedasticity-robust standard errors clustered at the firm level and Fama-MacBeth standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.6.2 Operating Performance

In the second stage, we examine the impact of *Solar Potential* and the associated proxy for transition risk *Carbon Offset* on the operational performance of REITs. Table 3.3 presents the regression results with the outcome variables ROA and ROE. As reported in Columns (1) and (3), we find a positive and significant relationship between REITs' *Solar Potential* and both ROA (1% significance level) and ROE (10% significance level) in the FM models, indicating that a greater solar potential leads to better operating performance. The estimated impact on firms' operating performance is economically significant. Considering a 50% increase in *Solar Potential* as depicted in the FM model in Column (1), we observe a corresponding rise in ROA by 5.92 basis points. Similarly, this increase is even more pronounced for ROE in Column (3), resulting in a rise of 24.9 basis points.

Although the estimated coefficients in the OLS models are directionally consistent with those in the FM models, we find no statistically significant relationship between *Solar Potential* and either ROA or ROE. The results of the FM model in Column (3) indicate a significant relationship (at the 1% level) between a REIT's potential to offset carbon emissions from grid electricity and operating performance. However, the other models in Columns (1), (2), and (4) do not corroborate this relationship. We attribute the discrepancies between the OLS and FM results to the models' different approaches to handling time-invariant firm characteristics and residual dependence. As outlined in the methodology section, the FM approach does not fully account for firm-specific heterogeneity, which influences the estimates of the coefficients and the standard errors. While there is some evidence consistent with prior literature suggesting that sustainable investments can enhance REIT operating performance, the overall statistical support in our models remains weak.

We attribute this weak evidence to two factors. First, a REIT's return should only be affected if solar panels are installed and generate additional revenue through direct and indirect cash flow channels; therefore, the potential for installation alone should not drive returns. The aforementioned special tax status of REITs and the lack of the ability to feed excess power into the grid are significant barriers to the widespread adoption of solar energy in the REIT sector. Nevertheless, we assume that our results are a reflection of a number of REITs already capitalizing on their potential. As highlighted by Lee and Liang (2024), the implementation of environmental regulations, such as emissions trading schemes not only raises expectations within the property sector, but also forces companies to deepen their commitment to sustainability strategies, which may include exploiting their solar potential. Moreover, as noted by Chmutina et al.

(2014), the adoption of solar systems is closely linked to environmental compliance and increasingly reflects the environmental concerns of market participants. Both of these factors may lead to solar installations gaining traction. We therefore expect an increasingly significant and more evident impact on operating performance in the coming years.

Second, notwithstanding the well-documented cash flow effects of sustainable investments at the property level, we do not anticipate a contemporaneous impact on operating performance at the firm level following the adoption of rooftop solar, particularly for REITs with larger property portfolios. As highlighted by Beracha et al. (2019), improving relative operating performance remains challenging for capital-intensive firms such as REITs. In our context, this could be particularly true for REITs implementing owner-operated strategies, as the upfront capital investment for solar systems could offset the operational benefits in the short term. In most cases, the installation of solar systems forms part of a REIT's holistic sustainability strategy and is aligned with property-level capital expenditure (CapEx) cycles. Such a holistic approach typically encompasses not only the investment in the solar installation itself but also additional expenditures aimed at advancing the technological automation of building operations, for example through smart meters or complementary energy-efficiency measures. As these types of investments are generally borne exclusively by the landlord, short-term cash flow effects are diluted. Consequently, there may be a non-negligible lag between the solar potential, its actual implementation, and the realization of financial benefits.

3.6.3 Firm Value

Finally, we regress our firm value variables on *Solar Potential* and *Carbon Offset*. The results are reported in Table 3.4. Controlling for size, leverage, investment strategy, operating performance and diversification, we find strong evidence for a positive relationship between the *Solar Potential* of a REIT and both M/B and P/NAV ratios in our cross-sectional and fixed effects regressions. The coefficients for all of the models are statistically significant at the 5% level, the 1% level, and the 10% level, respectively. We now also observe a considerably higher R-squared across models. Increasing a REIT's average available solar area by 50% results in a 0.49% higher P/NAV ratio in the FM model and a 0.73% higher P/NAV ratio in the fixed effects model, as presented in Columns (3) and (4). Given coefficients of 0.037 for the FM model and 0.079 for the fixed effects model in Columns (1) and (2), the same increase in solar potential would result in an even more pronounced improvement in the M/B ratio of 1.51% and 3.26%, respectively. Taking into account the relatively high standard deviation of *Solar Potential*

Table 3.3: Regression Results for Operating Performance

Variables	ROA		ROE	
	(1)	(2)	(3)	(4)
Solar potential (log)	0.146***	0.001	0.615*	0.166
	(0.044)	(0.074)	(0.353)	(0.346)
Carbon offset (log)	−0.424	0.571	−9.164***	−4.565
	(0.269)	(0.803)	(2.182)	(5.175)
Total assets (log)	0.350***	0.410***	0.810***	0.940*
	(0.018)	(0.050)	(0.284)	(0.496)
Firm age (log)	−0.054*	−0.084	1.454***	1.382***
	(0.031)	(0.056)	(0.407)	(0.170)
Real estate inv. growth$_{t-1}$	0.001	−0.005***	0.007	−0.022***
	(0.005)	(0.001)	(0.031)	(0.007)
D/E ratio$_{t-1}$	0.345***	0.234***	1.556***	1.510***
	(0.025)	(0.087)	(0.412)	(0.316)
Share buildings < 10 years	0.008**	0.011**	0.080***	0.080*
	(0.004)	(0.006)	(0.030)	(0.044)
Institutional ownership	0.002	0.004	0.240	0.314***
	(0.011)	(0.008)	(0.169)	(0.039)
GDP growth (MSA)	0.104***	0.098	1.597***	0.953
	(0.037)	(0.138)	(0.432)	(0.605)
HHI region	−0.898***	0.046	−2.897*	−1.628*
	(0.146)	(0.541)	(1.499)	(0.893)
HHI property type	−0.205	−0.429	−2.339	−2.726
	(0.141)	(0.736)	(2.407)	(3.087)
Constant	−2.040	−8.181	33.810*	4.498
	(1.648)	(5.196)	(17.585)	(37.277)
Coefficient estimates	FM	OLS	FM	OLS
Standard errors	FM	CL - F	FM	CL - F
Sector FE	N	Y	N	Y
Year FE	N	Y	N	Y
Observations	1,010	1,010	1,010	1,010
R-squared	0.189	0.322	0.151	0.161

The table reports the results of OLS and Fama-MacBeth regressions for the operating performance of U.S. equity REITs as a function of their solar potential and carbon offset and a vector of control variables. OLS regressions include both sector and year fixed effects. Heteroskedasticity-robust standard errors clustered at the firm level and Fama-MacBeth standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

within our sample, the results can be considered economically significant.

Unlike most listed companies in other sectors, REITs are subject to a double cost of equity capital due to the active trading of their underlying assets in the secondary market (Boudry et al., 2010). As a result, the *Solar Potential* and associated asset-level benefits may also be incorporated into appraisals, potentially reducing the transition risk premium of property yields as suggested by Leskinen et al. (2020). The relationship between property and firm values, as reflected in M/B and P/NAV, provides an understanding of the extent to which markets consider transition risk mitigation potential at both levels. The identified positive impact on both measures suggests that there are channels through which higher levels of *Solar Potential* affect valuation at the firm level beyond the book and market values of the underlying properties. Investors may therefore assume that solar systems enable management to increase a REIT's earnings over its existing property portfolio. As expected, we observe a larger impact on the M/B ratio, primarily due to the fact that depreciated book values, unlike NAVs, are less able to capture the potential benefits of sustainable features in property valuations.

Since corporate valuation is inherently forward-looking, the excess firm values can be seen as a reflection of investors' assumptions on REITs' future earnings. One possible reason for our findings is that investors might reasonably expect the benefits of on-site renewable energy generation to have an increasingly positive impact on property investments through income channels as the aforementioned barriers to REITs' installation of solar systems diminish. In addition to providing higher and more stable cash flows, REITs' *Solar Potential* is expected to influence growth rates of future earnings. This is particularly true for REITs with greater exposure to grids with higher electricity rates, where tenants benefit relatively more from energy cost savings related to the procurement of on-site renewable energy. Therefore, higher effective rental growth rates can be realized. This potential becomes even more important in states where the accelerating rise in electricity prices outpaces rental growth.

Higher firm values may also result from lower discount rates associated with a REIT's future earnings, which reflect lower transition risks due to higher on-site renewable energy potential. As transition risks are increasingly priced into commercial real estate markets, investors may face lower required returns for REITs with higher *Solar Potential*. Differences in return requirements are already evident among investors with a strong focus on environmentally sustainable properties, creating a clientele effect that is driving a valuation premium for greener assets (Fuerst et al., 2017). In addition, debt markets are placing greater emphasis on carbon performance and seeking to reduce their own financed emissions by incentivizing greener properties (An & Pivo, 2020;

Devine et al., 2024; Eichholtz, Holtermans, Kok, & Yönder, 2019; Leutner et al., 2024). As a result, investors expect lower refinancing risk for REITs with greater potential access green financing channels. While investors and lenders are expanding their criteria for evaluating the environmental performance of REITs to include indicators such as on-site renewable energy sources, we do not expect *Solar Potential* to have a significant signaling effect on firm values as it is less prominently communicated externally by most REITs, unlike green building certifications or benchmarking scores.

We also find a significant negative relationship between *Carbon Offset* and our dependent variables in both the FM and fixed effects models. Assuming a 10% increase in *Carbon Offset*, which implies a higher exposure to carbon-intensive grids, the M/B ratio experiences a notable reduction as can be seen in Columns (1) and (2). In the fixed effects model, with a coefficient of -0.734, the average decrease is 6.76%. The results of the FM model show an even stronger negative impact. Although less pronounced, the effect on P/NAV lies also in the same direction. Presented in Column (3), a 10% increase in the carbon intensity of the grid leads to a slight reduction in P/NAV of 0.97%. The difference in the size of the change in our two dependent variables could be due to the fact that a rise in electricity rates from grids with a higher share of fossil fuels has already been factored into NAVs.

Our models therefore suggest that REIT values are negatively affected by higher exposure to carbon-intensive grids. This is consistent with the findings of Bolton and Kacperczyk (2021), emphasizing that companies more dependent on fossil fuel-intensive energy sources are more vulnerable to technological transition risks posed by the emergence of cheaper renewable energy. Moreover, our results are in line with previous research showing that upstream emissions for which companies have no direct responsibility pose a significant transition risk for REITs. In the context of our primary explanatory variable, *Solar Potential*, our results underscore the sizable benefits to REITs of adopting solar systems. Importantly, the significant results for our two explanatory variables, *Solar Potential* and *Carbon Offset*, both in models with and without sector fixed effects, imply that transition risks and the ability to mitigate them through solar installations affect firm values across the REIT industry rather than individual sectors.

3.7 Robustness Checks

To validate our empirical results and therefore our research conclusions, we run a number of robustness checks. First, we perform a subsample analysis to assess the consistency of our findings across different firm sizes. As the solar potential of REITs should be unaffected by their financial performance, we do not expect reverse causality issues, widely discussed in the sustainability literature. However, it is conceivable that the market values the solar potential differently depending on the size of the company. It tends to be the larger REITs that publicly commit to net-zero goals and disclose more detailed information about their environmental performance, making them particularly attractive to green investors and funds. In addition, larger REITs may be able to take advantage of economies of scale in the implementation of solar strategies and benefit from more resources, especially in light of the challenges discussed above. To facilitate this analysis, we construct two portfolios by sorting REITs based on whether their total assets are above or below the median observed in our sample.

Second, we assess the reliability of our cross-sectional regressions by calculating coefficients using standard errors clustered by time. This method, as shown by Petersen (2008), yields standard errors that are similar to FM standard errors when properly specified, as both approaches account for cross-sectionally correlated residuals and the presence of time effects. It allows to detect a potential bias in our cross-sectional regressions due to potential firm effects significantly outweighing time effects.

Third, we examine the robustness of our results for firm values in the fixed effects models to potential unobserved confounders that may lead to omitted variable bias, an issue that has been extensively discussed in the existing literature on environmental-sustainable investments and firm performance. We therefore conduct a sensitivity analysis following Cinelli and Hazlett (2020), which measures how influential a potential confounder needs to be in order to significantly reduce the impact of our independent variables and thus cause a change in our research results.

Table 3.4: Regression Results for Firm Values

Variables	M/B ratio (log)		P/NAV ratio (log)	
	(1)	(2)	(3)	(4)
Solar potential (log)	0.037**	0.079***	0.012*	0.018***
	(0.017)	(0.025)	(0.006)	(0.004)
Carbon offset (log)	−1.037***	−0.734***	−0.102***	−0.062
	(0.077)	(0.159)	(0.034)	(0.048)
Total assets (log)	0.007	0.027*	−0.012**	−0.008***
	(0.009)	(0.015)	(0.005)	(0.002)
Firm age (log)	0.165***	0.128***	0.032***	0.020***
	(0.013)	(0.027)	(0.007)	(0.004)
Real estate inv. growth$_{t-1}$	0.005***	0.002*	0.001***	0.001***
	(0.001)	(0.001)	(0.0004)	(0.00005)
D/E ratio$_{t-1}$	0.242***	0.222***	−0.010*	−0.017***
	(0.011)	(0.028)	(0.005)	(0.001)
ROA$_{t-1}$	0.128***	0.096***	0.012***	0.007***
	(0.016)	(0.015)	(0.003)	(0.0002)
Share buildings < 10 years	0.002**	0.003	−0.0003	−0.0002
	(0.001)	(0.003)	(0.001)	(0.0002)
Institutional ownership	−0.003	−0.008**	0.004***	0.003***
	(0.006)	(0.004)	(0.001)	(0.001)
GDP growth (MSA)	0.028	0.007	0.0003	−0.004
	(0.018)	(0.047)	(0.005)	(0.011)
HHI region	−0.120	−0.118	−0.094***	−0.059*
	(0.076)	(0.123)	(0.036)	(0.036)
HHI property type	0.073	−0.108	0.018	0.012
	(0.057)	(0.127)	(0.024)	(0.027)
Constant	5.671***	3.748***	5.071***	4.884***
	(0.474)	(1.221)	(0.229)	(0.260)
Coefficient estimates	FM	OLS	FM	OLS
Standard errors	FM	CL - F	FM	CL - F
Sector FE	N	Y	N	Y
Year FE	N	Y	N	Y
Observations	1,010	1,010	1,010	1,010
R-squared	0.435	0.503	0.376	0.354

The table reports the results of OLS and Fama-MacBeth regressions for the firm value variables of U.S. equity REITs as a function of their solar potential and carbon offset and a vector of control variables. OLS regressions include both sector and year fixed effects. Heteroskedasticity-robust standard errors clustered at the firm level and Fama-MacBeth standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.5 shows the results of our subsample analysis. While we lose some statistical significance for both *Solar Potential* and *Carbon Offset* in the models shown in Columns (2) and (7) compared to our initial coefficient estimates, the results do not support the hypothesis that *Solar Potential* may command a larger firm value premium for larger REITs. Instead, since both smaller and larger REITs are affected by the observed changes and the significance of the control variables in the models decreases for both subsamples, we attribute these results to the reduced sample size within our portfolios. In the other models, however, we find significant coefficient estimates for both *Solar Potential* and *Carbon Offset* that are consistent with the size and direction of our initial estimates shown in Table 3.4. Importantly, our overall results remain consistent even when the sample size is reduced by half, indicating that the observed estimates are not driven by heterogeneity and specific portions in the data. This suggests that the market prices in the ability to mitigate transition risks and thus financially benefit from future rooftop solar deployment, irrespective of firm size.

The results of the OLS models with time-clustered standard errors are reported in Table 3.6, showing that both the size and direction of the coefficient estimates and standard errors are consistent with the results of the FM regressions. As highlighted by Petersen (2008), the estimates obtained from OLS and FM regressions may be very similar even when the bias due to a firm effect is large. However, the author also notes that in the presence of a bias, the FM model in particular would significantly underestimate true standard errors, to an even greater extent than the OLS model, which is not the case in our results. Comparing both the FM and time-clustered standard errors with the firm-clustered standard errors of the fixed effects models in Tables 3.2, 3.3 and 3.4, the latter tend to be higher, although the difference is not large. While the variation in standard errors between the results suggests a somewhat stronger influence of the firm effect, which is to be expected given the structure of our dataset, we consider the estimates of the FM models to be robust given the size of the effect.

Table 3.5: Subsample Analysis for Firm Values

Variables	M/B ratio (log)		P/NAV ratio (log)		M/B ratio (log)		P/NAV ratio (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar potential (log)	0.067***	0.032	0.019**	0.041***	0.064*	0.028**	−0.006	0.018**
	(0.022)	(0.020)	(0.009)	(0.006)	(0.033)	(0.017)	(0.014)	(0.007)
Carbon offset (log)	−0.935***	−0.271*	−0.093***	−0.048	−1.016***	−0.627***	−0.034	−0.089
	(0.145)	(0.146)	(0.035)	(0.085)	(0.079)	(0.226)	(0.064)	(0.073)
Total assets (log)	0.079***	0.058***	−0.012	0.0004	0.165***	0.188***	0.015	0.026**
	(0.024)	(0.012)	(0.008)	(0.004)	(0.013)	(0.017)	(0.012)	(0.011)
Firm age (log)	0.166***	0.180***	0.040**	0.016***	0.145***	0.097***	0.028**	0.025***
	(0.020)	(0.033)	(0.021)	(0.006)	(0.018)	(0.019)	(0.011)	(0.003)
Real estate inv. growth$_{t-1}$	0.006*	0.002*	0.001**	0.0003***	0.005**	0.0004	0.001*	0.0004***
	(0.003)	(0.001)	(0.0003)	(0.0001)	(0.002)	(0.001)	(0.0003)	(0.0001)
D/E ratio$_{t-1}$	0.220***	0.169***	−0.019***	−0.024***	0.177***	0.182***	−0.014*	−0.027***
	(0.026)	(0.034)	(0.006)	(0.002)	(0.036)	(0.027)	(0.008)	(0.002)
ROA$_{t-1}$	0.061**	0.050***	0.002	−0.002	0.218***	0.160***	0.019***	0.009***
	(0.029)	(0.018)	(0.005)	(0.002)	(0.021)	(0.011)	(0.004)	(0.001)
Share buildings < 10 years	0.006*	0.009*	−0.0001	0.0005	−0.001	−0.002	−0.001*	−0.001**
	(0.003)	(0.005)	(0.001)	(0.0004)	(0.002)	(0.001)	(0.0004)	(0.0003)
Institutional ownership	−0.001	−0.001	0.006***	0.002***	−0.001	−0.002	−0.001*	−0.001**
	(0.010)	(0.004)	(0.002)	(0.0004)	(0.012)	(0.009)	(0.003)	(0.001)
GDP growth (MSA)	−0.058**	−0.006	0.003	−0.008	0.155***	0.077*	−0.005	0.013
	(0.029)	(0.041)	(0.006)	(0.012)	(0.016)	(0.040)	(0.008)	(0.014)
HHI region	0.446***	0.735***	−0.026	−0.040	0.046	−0.074	−0.124***	−0.014
	(0.114)	(0.284)	(0.036)	(0.052)	(0.137)	(0.169)	(0.040)	(0.031)
HHI property type	0.157	−0.231	0.017	0.037	0.484***	0.147***	−0.006	0.087***
	(0.110)	(0.143)	(0.025)	(0.038)	(0.169)	(0.048)	(0.057)	(0.033)
Constant	3.948***	0.770	4.916***	4.552***	2.592***	0.799	4.403***	4.390***
	(0.786)	(0.773)	(0.269)	(0.542)	(0.562)	(0.901)	(0.372)	(0.473)
Subsample	< Median	< Median	< Median	< Median	> Median	> Median	> Median	> Median
Coefficient estimates	FM	OLS	FM	OLS	FM	OLS	FM	OLS
Standard errors	FM	CL - F	FM	CL - F	FM	CL - F	FM	CL - F
Sector FE	N	Y	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y	N	Y
Observations	505	505	505	505	505	505	505	505
R-squared	0.450	0.487	0.411	0.369	0.610	0.687	0.463	0.445

The table shows the regression results of the subsample analysis for firm values of U.S. equity REITs as a function of their solar potential and carbon offset and vector of control variables. Subsamples are defined according to the median firm size in our sample as measured by total assets. OLS regressions include both sector and year fixed effects. Heteroskedasticity-robust standard errors clustered at the firm level and Fama-MacBeth standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.6: Robustness Checks for Cross-Sectional Regressions

Variables	Alpha	Beta (log)	ROA	ROE	M/B ratio (log)	P/NAV ratio (log)
	(1)	(2)	(3)	(4)	(5)	(6)
Solar potential (log)	0.226	0.022	0.159***	0.723**	0.046***	0.012**
	(0.341)	(0.019)	(0.044)	(0.368)	(0.015)	(0.006)
Carbon offset (log)	−3.522*	0.206	−0.584**	−9.891***	−1.154***	−0.124***
	(2.075)	(0.155)	(0.255)	(1.742)	(0.089)	(0.038)
Total assets (log)	−0.707**	0.043	0.343***	0.851***	−0.004	−0.014**
	(0.321)	(0.028)	(0.022)	(0.242)	(0.012)	(0.006)
Firm age (log)	0.215	0.012	−0.105***	0.974***	0.150***	0.020***
	(0.393)	(0.034)	(0.028)	(0.374)	(0.012)	(0.007)
Real estate inv. growth$_{t-1}$	0.046**	−0.002	−0.001	0.002	0.004***	0.001***
	(0.019)	(0.001)	(0.003)	(0.022)	(0.001)	(0.0003)
D/E ratio$_{t-1}$	0.302	0.019*	0.310***	1.416***	0.237***	−0.011*
	(0.214)	(0.010)	(0.026)	(0.344)	(0.013)	(0.006)
ROA$_{t-1}$	0.518*	−0.021			0.128***	0.013***
	(0.301)	(0.020)			(0.012)	(0.005)
Share buildings < 10 years	−0.022	−0.001	0.006*	0.068**	0.002*	−0.0004
	(0.026)	(0.002)	(0.004)	(0.030)	(0.001)	(0.001)
GDP growth (MSA)	0.559	−0.036	0.120***	1.756***	0.041***	0.002
	(0.424)	(0.040)	(0.038)	(0.386)	(0.016)	(0.005)
Institutional ownership	0.022	0.018***	0.004	0.311**	−0.0003	0.003***
	(0.095)	(0.006)	(0.010)	(0.132)	(0.006)	(0.001)
HHI region	−2.801	0.219***	−0.958***	−2.790**	−0.166**	−0.110***
	(1.994)	(0.083)	(0.164)	(1.333)	(0.084)	(0.034)
HHI property type	1.539	0.253***	−0.229*	−1.949	0.077	0.005
	(1.252)	(0.085)	(0.138)	(2.336)	(0.051)	(0.023)
Constant	26.724*	−2.864***	−0.838	36.838***	6.482***	5.298***
	(15.468)	(1.004)	(1.322)	(13.618)	(0.657)	(0.268)
Coefficient estimates	OLS	OLS	OLS	OLS	OLS	OLS
Standard errors	CL - T	CL - T	CL - T	CL - T	CL - T	CL - T
Sector FE	N	N	N	N	N	N
Year FE	N	N	N	N	N	N
Observations	1,010	1,010	1,010	1,010	1,010	1,010
R-squared	0.049	0.045	0.181	0.091	0.390	0.105

The table shows the regression results of the robustness checks for stock performance, operating performance and firm value of U.S. equity REITs as a function of their solar potential and carbon offset and vector of control variables. For direct comparison with the Fama-MacBeth regression results, the coefficients are estimated without time and sector fixed effects. Time-clustered robust standard errors are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively

Tables 3.7 and 3.8 present the sensitivity statistics for our independent variables P/NAV and price-to-book (P/B). We estimate the strength of potential confounders using statistically significant covariates with high explanatory power for firm values identified in our fixed effects regressions. The robustness bounds $R^2_{Y\sim Z|\mathbf{X},D}$ and $R^2_{D\sim Z|\mathbf{X}}$ indicate the maximum residual variation in the outcome and treatment variables that could be explained by a omitted variable in an extreme scenario. The strength of a potential omitted variable is assessed by the explanatory power of the controls, firm age, ROA, and real estate investment growth. Comparing the robustness bounds to the robustness values ($RV_{q=1}$) of our key independent variables, we find the robustness values exceeding the robustness bounds in all setups. It can be seen that only the robustness bound of ROA indicates that a possible confounder in an extreme scenario could have a significant impact on the coefficient estimate of *Solar Potential*. However, overall results suggest that potential omitted variables may not be strong enough to fully explain the effects of *Solar Potential* and *Carbon Offset*. Figure 3.2 shows sensitivity plots of the point estimates of our key independent variables with a potential confounder as strong as ROA. For this analysis, we specifically chose ROA because, as noted above, this covariate has the highest confounding power in extreme scenarios. Similar to the sensitivity statistics, the sensitivity plots show high robustness in both the strength and direction of the point estimates of *Solar Potential* and *Carbon Offset* to a potential omitted variable that is k times stronger than ROA. Even in an extreme scenario where a potential confounder is three times stronger than ROA, only the point estimate of *Solar Potential* with the outcome variable P/B ratio would experience a change in coefficient direction. In addition, the vertical axis of the sensitivity plots indicates that the potential confounders and control variables in our models have significantly higher explanatory power for the residual variation of firm values than for the residual variation of our explanatory variables. The results therefore suggest that *Solar Potential* and *Carbon Offset* are robust to potential omitted variables and, importantly, they are not merely proxies for omitted financial firm characteristics.

Another potential concern is that more profitable REITs may selectively invest in properties with higher solar potential, creating endogeneity concerns. However, *Solar Potential* in our framework is largely determined by REITs' asset type and geographic focus, making such reallocation unlikely within our study period. The sensitivity analysis (Tables 3.7 and 3.8) further indicates that omitted firm characteristics (including profitability-driven selection) would require implausibly strong explanatory power to change the direction of our results. While future work could benefit from additional approaches, such as instrumental variable strategies, to address potential endogeneity, our findings appear robust against this concern.

Table 3.7: Sensitivity Statistics for P/NAV Ratio

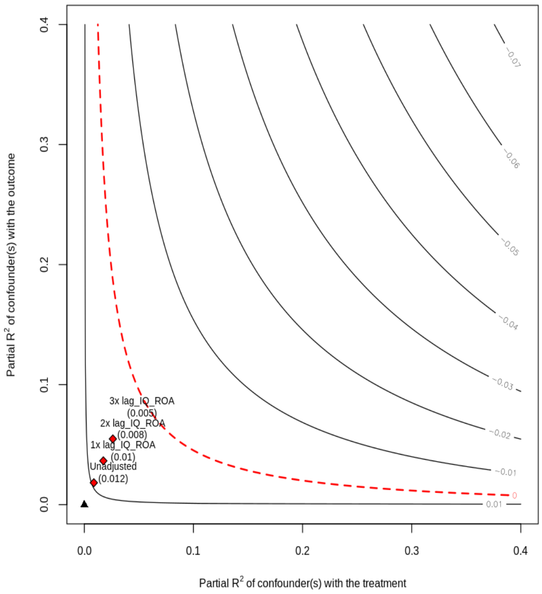
Outcome: *P/NAV ratio*						
Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Solar potential (log)	0.012	0.005	2.238	0.5%	6.8%	0.9%
df = 997	*Bound 1x*	*Firm age (log)*: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 1.3%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.4%				
Carbon offset (log)	-0.124	0.045	-2.767	0.8%	8.4%	2.5%
df = 997	*Bound 1x*	*Firm age (log)*: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 1.3%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0%				
Solar potential (log)	0.012	0.005	2.238	0.5%	6.8%	0.9%
df = 997	*Bound 1x*	ROA_{t-1}: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 1.8%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.9%				
Carbon offset (log)	-0.124	0.045	-2.767	0.8%	8.4%	2.5%
df = 997	*Bound 1x*	ROA_{t-1}: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 1.8%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.2%				
Solar potential (log)	0.012	0.005	2.238	0.5%	6.8%	0.9%
df = 997	*Bound 1x*	*RE inv. growth*$_{t-1}$: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 2.2%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.7%				
Carbon offset (log)	-0.124	0.045	-2.767	0.8%	8.4%	2.5%
df = 997	*Bound 1x*	*RE inv. growth*$_{t-1}$: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 2.1%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0%				

The table shows the robustness report with the sensitivity statistics for the outcome variable P/NAV ratio. It includes the partial R^2 of the treatment with the outcome and the robustness value $RV_{q=1}$. The bounds indicate the strength of an unobserved confounder that has the same effect on the treatment variables (solar potential or carbon offset) as the observed covariates. An *RV* above either bound indicates that a potential confounder is not strong enough to remove the explanatory power of the treatment variables.

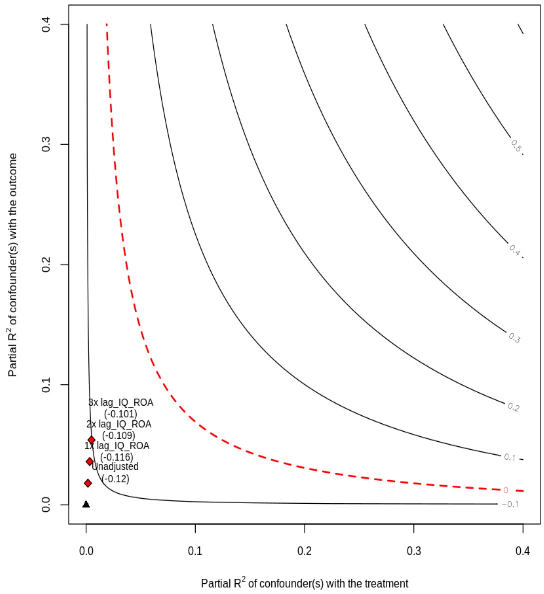
Table 3.8: Sensitivity Statistics for P/B Ratio

Outcome: *P/B ratio*						
Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Solar potential (log)	0.046	0.019	2.456	0.6%	7.5%	1.5%
df = 997	*Bound 1x*	*Firm age (log)*: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 5.6%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.4%				
Carbon offset (log)	-1.154	0.159	-7.246	5%	20.5%	15.4%
df = 997	*Bound 1x*	*Firm age (log)*: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 5.6%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0%				
Solar potential (log)	0.046	0.019	2.456	0.6%	7.5%	1.5%
df = 997	*Bound 1x*	ROA_{t-1}: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 13.8%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.9%				
Carbon offset (log)	-1.154	0.159	-7.246	5%	20.5%	15.4%
df = 997	*Bound 1x*	ROA_{t-1}: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 13.6%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.2%				
Solar potential (log)	0.046	0.019	2.456	0.6%	7.5%	1.5%
df = 997	*Bound 1x*	*RE inv. growth*$_{t-1}$: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 2.8%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0.7%				
Carbon offset (log)	-1.154	0.159	-7.246	5%	20.5%	15.4%
df = 997	*Bound 1x*	*RE inv. growth*$_{t-1}$: $R^2_{Y\sim Z\|\mathbf{X},D}$ = 2.8%, $R^2_{D\sim Z\|\mathbf{X}}$ = 0%				

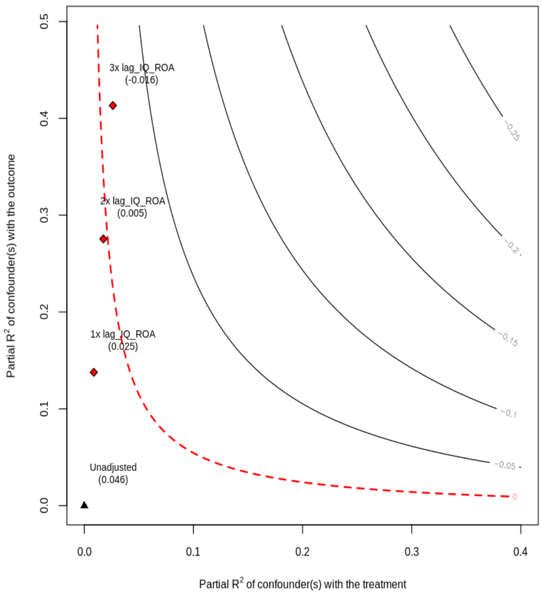
The table shows the robustness report with the sensitivity statistics for the outcome variable P/B ratio. It includes the partial R^2 of the treatment with the outcome and the robustness value $RV_{q=1}$. The bounds indicate the strength of an unobserved confounder that has the same effect on the treatment variables (solar potential or carbon offset) as the observed covariates. An *RV* above either bound indicates that a potential confounder is not strong enough to remove the explanatory power of the treatment variables.



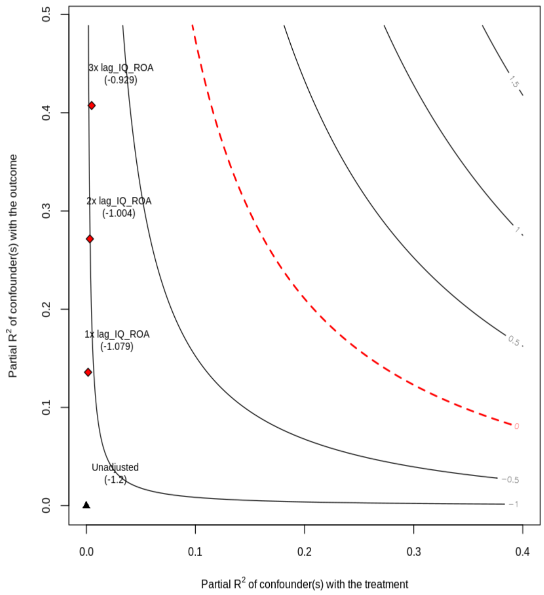
(a) Point estimate of solar potential with the outcome variable P/NAV ratio



(b) Point estimate of carbon offset with the outcome variable P/NAV ratio



(c) Point estimate of solar potential with the outcome variable P/B ratio



(d) Point estimate of carbon offset with the outcome variable P/B ratio

Figure 3.2: Sensitivity contour plots in the partial R^2 scale of unobserved confounders. The figure plots the sensitivity of the point estimates to potential confounders k times stronger than ROA. The horizontal axis shows how strongly the confounder is associated with the treatment variables (solar potential or carbon offset). The vertical axis shows how strongly the confounder is associated with the outcome variables (P/NAV ratio or P/B ratio).

3.8 Concluding Remarks

Building on prior literature that highlights the influence of carbon emissions and mitigation strategies on asset prices, this study advances the understanding of how carbon-transition risks affect the financial performance of REITs. Our approach contributes to the REIT literature by extending environmental performance metrics beyond conventional benchmarking and green building certification schemes. Specifically, we employ a unique dataset that combines rooftop solar potential across REIT portfolios with a REIT-specific carbon offset factor. This offset factor captures each company's reliance on carbon-intensive electricity grids and the potential for solar adoption to reduce carbon emissions by displacing grid electricity. In doing so, we provide the first evidence on whether rooftop solar potential can serve as a driver of REITs' stock performance, operating performance and firm values.

Our analysis of stock performance indicates that markets do not yet fully incorporate REITs' solar adoption potential, as evidenced by the lack of significant effects on alphas and market betas. We attribute this primarily to the limited deployment of rooftop solar within the sector, driven in part by regulatory barriers that have slowed adoption. This limited uptake also helps explain the weak evidence of effects on operating performance. Furthermore, the substantial upfront capital expenditures required for owner-operated solar projects and associated building technology upgrades may offset the immediate, near-term revenue gains, further dampening short-term cash flow benefits.

We find strong evidence that REITs' solar potential has a significant effect on firm values, producing a valuation premium that extends beyond the market and book values of the underlying property portfolios. Importantly, this effect is not a simple proxy for omitted financial characteristics. While solar potential does not have the same direct signaling power as certification measures, investors appear to value REITs' future earnings more highly because of the anticipated financial benefits associated with solar adoption. At the same time, higher valuations may reflect lower required rates of return as markets price in reduced transition risk, including future carbon costs. The significant relationship between carbon offset factors and firm valuation further supports the existing literature that REITs face transition risks not only from their direct emissions but also from upstream emissions tied to local grids.

For REIT management, these findings highlight that markets already incorporate solar potential in firm valuations, even though adoption barriers have muted short-term operating results. This underscores the strategic importance of prioritizing assets connected to carbon-intensive grids, where solar investments can deliver both financial gains—through tax credit transfers–and reduced transition risk. Integrating solar potential into portfolio strategies and disclosure practices can enhance ESG signaling, lower capital costs and strengthen investor confidence. For investors, accounting for REITs' solar potential offers both improved long-term total returns and enhanced ESG performance. REITs that pursue solar strategies while managing third-party capital can also deliver competitive advantages through enhanced operational efficiency and access to leading real estate asset management expertise.

For policymakers, the gap between valuation premia and limited adoption suggests regulatory obstacles remain. Targeted measures—such as simplifying grid integration, streamlining permitting processes and supporting tenant electricity models—could accelerate solar deployment in carbon-intensive regions. The rise of community rooftop solar projects also presents opportunities for shared benefits, enabling REITs, companies and residents to access greener and more affordable energy.

Overall, our results point to a significant and robust relationship between REITs' solar potential and firm values, though our analysis is subject to specific data limitations. As more REITs adopt solar strategies, richer data on realized outcomes could provide deeper insights into the income and capital channels through which financial benefits materialize. More granular data on spatial adoption patterns would also help capture the political and geographical factors influencing REITs' utilization of rooftop solar. With broader adoption, we expect future research to uncover stronger effects on both stock performance and operating outcomes. In addition, further analysis could explore how REIT sectors with limited rooftop solar capacity might leverage alternative renewable strategies—such as solar facades or off-site renewable energy projects—to mitigate transition risks at the firm level.

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4 Unveiling the Impact of SFDR on Unlisted Real Estate Funds: A J-Curve and Panel Regression Analysis

4.1 Abstract

Purpose: This paper investigates the relationship between the Sustainable Finance Disclosure Regulation (SFDR) and the performance of unlisted real estate funds.
Design/methodology/approach: While existing literature has primarily focused on the impact of voluntary sustainability disclosure, such as certifications or reporting standards, this study addresses a significant research gap by constructing and analyzing the financial J-Curve of 40 funds under the SFDR. The authors employ a panel regression analysis to examine the effects of different SFDR categories on fund performance.
Findings: The findings reveal that funds categorized under Article 8 of the SFDR do not exhibit significantly poorer performance compared to funds categorized under Article 6 during the initial phase after launch. On average, Article 8 funds even demonstrate positive returns earlier than their peers. However, the panel regression analysis suggests that Article 8 funds slightly underperform when compared to Article 6 funds over time.
Practical implications: While investors may not anticipate lower initial returns when opting for higher SFDR categories, they should nevertheless be aware of the shortcomings inherent in the existing SFDR labeling system, particularly in the context of unlisted real estate.
Originality: To the best of our knowledge, this study represents the first quantitative examination of unlisted real estate fund performance under the SFDR. By providing unique insights into the J-Curves of funds, our research contributes to the existing body of knowledge on the impact of sustainability regulations in the financial sector.

Keywords: *SFDR; Unlisted Real Estate; J-Curve, Performance.*

4.2 Introduction and Background

Building on the objectives set out in Action 9, "Strengthening sustainability disclosure and accounting rule-making" of the action plan on financing sustainable growth, the European Commission introduced the sustainable finance disclosure regulation (SFDR) in Regulation (EU) 2019/2088 in 2019. This regulation became mandatory for all member states in March 2021. The basis for these efforts is the EU's goal of directing private capital flows toward sustainability to meet the Paris Agreement climate goals. The regulation primarily affects European financial market participants and advisors and has the subsidiary goal of harmonizing sustainability requirements and reducing information asymmetries arising from sustainability risks and impacts in principal–agent relationships (such as between fund managers and investors). The SFDR provisions are intended to provide investors with the information they need to make informed decisions and implement their own sustainability efforts and are subject to a uniformly established legislation as opposed to voluntary scorings, benchmarks or certifications (European Parliament and Council, 2019). Aligned with the disclosure requirements of the EU taxonomy, the SFDR serves as a supplementary measure to complement climate policies, such as the EU-ETS or emission standards for buildings, rather than acting as a direct substitute (Schütze & Stede, 2021). Generally, the SFDR provisions require reporting based on three categories, each with different criteria to be considered and disclosed:

- Article 6 products, which have no specific sustainability features;
- Article 8 products, which have environmental or social characteristics; and
- Article 9 products, which pursue specific sustainability objectives.

The categorization into Articles 6, 8 and 9 is derived from the principles-based requirements (PBR) of Level 1 SFDR, supplemented by the more detailed specifications provided in the Regulatory Technical Standards (RTS) of Level 2 SFDR. The RTS serve as guidelines for dealing practically with the scope, methods and disclosure requirements of each category. For Article 6 products, it is mandatory to include ESG risk assessments in the decision-making process or declare if no relevant risks are identified. This allows Article 6 funds to exhibit a spectrum of ESG ambitions, ranging from very low to very high. Article 8 products promote environmental or social characteristics and sustainable investments, without making sustainable investments the primary objective of the product. Additionally, sustainable investments do not significantly harm any objectives outlined in the EU-Taxonomy. Article 9 expands on the foundation set by Article 8 by requiring that properties in the portfolio meet strict sustainability criteria throughout the holding period. These criteria prioritize operational efficiency over the entire life-cycle, resulting in a significant portion of Article 9 funds being allocated to highly efficient new buildings (European Parliament and Council, 2019; INREV, 2023). The associated principal adverse impacts (PAIs) arise from Annex I of the RTS and are divided into mandatory and voluntary indicators, of which, according to the European Association for Investors in Non-Listed Real Estate Vehicles (INREV, 2023), currently only seven are applicable to real estate. These indicators are intended to provide practical guidance on how to report on ESG issues and are currently the subject of intense debate.

Real estate is traditionally an asset class in which investments are predominantly made directly or through unlisted funds. Only about one-tenth of the $36.2 trillion global commercial real estate market is listed real estate (European Public Real Estate Association, 2023). Since approximately 40% of all greenhouse gas emissions can be directly attributed to the real estate sector, the alignment of private capital flows is thus a crucial factor for decarbonizing the property sector (European Commission, 2019). The introduction of the SFDR has resulted in existing investment funds embarking on an intensive rebranding process, seeking to capitalize on the advantages associated with early adoption of a higher SFDR category (Cremasco & Boni, 2022). Although there is no legal obligation for a minimum category for real estate funds, a category of at least Article 8 SFDR has been emerging as a basic market requirement for real estate-related investment products as most institutional investors attach increasing importance to KPIs for measuring sustainability. With regard to voluntary standards like GRESB, sizable funds have typically functioned as early adopters, positioning themselves to enjoy the benefits of enhanced financial performance in the form of elevated total returns (Brounen & van der Spek, 2017). Extensive early adoption of higher SFDR categories is underscored by the observation that nearly half of real estate funds are already categorized under Article 8 or Article 9 SFDR (PricewaterhouseCoopers, 2023). This share might increase even further especially if there is evidence that a higher SFDR category is not economically disadvantageous compared to the default category. While Chegut et al. (2019) point out the absence of conclusive evidence concerning disparities in input costs between green and conventional properties, the prevailing sentiment among investors and developers indicates a widely held belief that sustainability is associated with higher upfront expenses. This perception is particularly prominent in the context of renovating existing buildings. From a fund management perspective, it is important to consider whether opting for a higher SFDR category will negatively impact initial fund performance. This assessment becomes even more crucial when factoring in the additional costs of fund reporting and documentation required by SFDR regulations. On the other hand, there might be advantages in the form of increased fund inflows due to positive signaling effects or a conservative risk-return profile resulting from the tendency toward newer and high-quality properties contained in Articles 8 and 9 funds. While voluntary disclosure in the realm of unlisted real estate funds has only gained traction in recent years, the introduction of the SFDR and the associated mandatory disclosure contains uninvestigated implications for investors. In contrast to prior research, predominantly centering on voluntary standards such as benchmarks and certifications, a notable research gap exists regarding the impact of disclosure regulations on fund performance in instances where fund managers do not explicitly and voluntarily opt for such standards. This study seeks to address this gap through a thorough empirical investigation utilizing a dataset comprising unlisted real estate funds categorized under the SFDR. Recognizing the nuanced and phase-specific nature of returns in the early stages of unlisted funds, we adopt a two-part methodology. The first part of our study focuses on the initial fund performance by assessing J-Curve characteristics based on SFDR categorization. Subsequently, employing panel data analysis, the second part seeks to ascertain the significance of the SFDR category's impact on the overall fund performance. At the same time, the study highlights potential shortcomings of the SFDR within the realm of real estate investment. The paper ends by presenting our conclusions.

4.3 Literature Review

An extensive body of existing literature deals with the implications of voluntary green building certifications at property level. In the commercial real estate sector, many studies reveal green premiums for office buildings in terms of rents, values, and prices (Wiley et al., 2010; Eichholtz et al., 2010; Fuerst & McAllister, 2011; Reichardt et al., 2012; Eichholtz et al., 2013; Chegut et al., 2014; Holtermans & Kok, 2019). A green premium in the income and capital component of properties can also be observed for both single- and multi-family homes (Kahn & Kok, 2014; Bond & Devine, 2016; Cadena & Thomson, 2021; Dell'Anna & Bottero, 2021). Moreover, certifications for building sustainability also exert a favorable impact on operational performance, as evidenced by an enhanced occupancy rates (Fuerst & McAllister, 2009; Devine & Kok, 2015). Green premiums are not confined solely to mature and highly liquid commercial real estate markets; they are also evident in emerging real estate markets (Lambourne, 2022; Costa et al., 2017). The green premium observed in both the income and capital components of properties may benefit the financial performance of funds with a higher SFDR category, which typically hold newer and more certified properties.

Another body in the field of sustainable real estate focus on performance and valuation metrics of listed real estate companies at corporate level. The impact of voluntary corporate sustainability reporting standards can be used to infer the potential implications of a mandatory reporting standards such as the SFDR. In both cases, a higher level of (perceived) disclosure leads to greater transparency for lenders and investors. Ansari et al. (2015) find evidence that sustainability reporting based on the GRI standards has a positive impact on both market values and abnormal returns of listed real estate companies. Feng and Wu (2021) provide similar findings for the GRESB reporting standard. Moreover, they show that higher disclosure levels are associated with better credit ratings, higher unsecured debt ratios and lower cost of debt financing. In addition to sustainability reporting, higher ESG ratings also have a positive impact on listed real estate companies. Brounen et al. (2021) indicate that more transparent ESG performance data in the EPRA sBPR database leads to a return premium for listed real estate companies since investors are able to make more informed investment decisions. However, Cajias et al. (2014) attribute differences in valuations of real estate companies to ESG concerns which negatively affect firm value rather than ESG strengths that lead to a sustainability premium. Furthermore, their findings suggest that high ESG ratings negatively impact returns as high ESG ratings may not translate into better operational performance in the short run. While public markets presently incorporate any ESG changes, the real impact on companies' operational performance may exhibit lagging effects.

It is not only the sustainability disclosure and rating of the company itself that has an impact at firm level but also the sustainability of the properties owned by the companies. Sustainability in this context usually refers to properties' environmental performance. Although there is evidence that non-green REITs outperform their green peers, most research highlights the benefits of environmentally friendly property features (Coën et al., 2018; Mariani et al., 2018). Holding greener properties can improve REITs' performance metrics at the operational level, such as return on assets, return on equity, and funds from operations (Eichholtz et al., 2012; Fuerst, 2015; Ooi & Dung, 2019; Morri et al., 2021). Furthermore, REITs with a greener portfolio are valued at a premium and are subject to less systematic risk (Eichholtz et al., 2012; Sah et al., 2013; Fuerst, 2015). Beyond higher firm values, Sah et al. (2013) observe better performance of stock values compared to less green REITs. Greener portfolios are also associated with lower borrowing costs (An & Pivo, 2020; Leutner et al., 2024). Both the bonds issued by REITs and the bonds trading on the secondary market exhibit smaller spreads (Eichholtz et al., 2019). Similarly, the cost of equity tends to be lower for greener REITs (Hsieh et al., 2020). Devine and Yönder (2023) reveal that the benefits experienced by greener REITs can, to some extent, be attributed solely to reputational factors. In the context of the SFDR, setting Article 8 as the minimum category for the market also creates a signaling effect. While directing more investor capital towards Article 8 and 9 funds may enhance financial performance, it does not necessarily imply superior sustainability performance (Cremasco & Boni, 2022).

Given the lack of available data, there are only a limited number of studies in the field of sustainable real estate that specifically address the impact of unlisted fund disclosure on returns. Existing research focuses on voluntary disclosure initiatives, yet there exists a gap in the literature addressing emerging mandatory standards such as SFDR. Brounen and van der Spek (2017) demonstrate that better total GRESB scores not only result in higher excess total returns but can also account for fluctuations in unlisted fund returns in the absence of other explanatory fund variables. This implies that even without considering crucial fund characteristics such as leverage, investors can elucidate variations using GRESB scores. However, it is worth noting that the effects between disclosure and fund performance are lagged, given that fund reporting is typically retrospective. Devine et al. (2022) find that both GRESB participation and GRESB scores have explanatory power for fund returns. Regarding total returns, the impact is discernible solely in the capital component, with no observable effect in the income component. Additionally, it is noteworthy that the relationships between fund returns and both GRESB participation and scores persist unaffected by local economic conditions. Research by Brounen and van der Spek (2023) shows that GRESB participation explains superior performance in unlisted fund returns. However, higher GRESB scores do not necessarily trigger higher returns. Rather, it is the specific environmental sub-scores of individual funds and their overall GRESB performance which contribute to an increase in returns.

Within the broader economic literature, there is evidence supporting the aforementioned signaling effects associated with a higher SFDR category and its impact on mutual funds. Becker et al. (2022) highlight that the implementation of SFDR has a discernible impact on fund inflows within the first four months after its introduction. In particular, Articles 8 and 9 funds experience positive net inflows compared to Article 6 funds. However, Ferriani (2023) notes that the benefits of a higher SFDR category, reflected in higher net inflows and improved returns, are limited to Article 9 funds. In addition to its financial impact, the effectiveness of SFDR from a sustainability perspective is crucial. Cremasco and Boni (2022) indicate that despite the innovations introduced by the SFDR, the European financial market is still characterized by ambiguity and indistinct categorization. Their results show that a distinction between Article 6 and Article 9 funds based on internal incentive structures for managers reveals a cross-category pattern of financial and sustainability performance. The authors express concerns about potential greenwashing practices due to the ambiguity surrounding actual sustainability within the SFDR categories in the financial context. The main section of our paper provides additional information on this matter and its practical implications.

To best of our knowledge, the present work is the first to explore the impact of mandatory regulations (such as the SFDR) on unlisted real estate funds, thereby creating a new research thread. We expect more future research in this field due to increasingly stringent standards for unlisted real estate.

4.4 Data and Descriptive Analysis

The dataset is provided by one of the largest European service capital investment companies specializing in the setup and management of regulated real estate funds on behalf of third parties. Thus, it can be inferred that the funds analyzed in our study represent a significant sample size compared to the market size of funds recently launched around the time of the introduction of the SFDR. The dataset constitutes an unbalanced panel dataset with monthly observations from March 2021 to March 2023. To allow for a rigorous empirical analysis, we cleaned the original dataset of 54 funds by excluding observations that prevent a comprehensive analysis over the entire review period. Our final dataset thus consists of 40 funds, all of which—for the purpose of examining initial periods and the relationship between fund launches and the SFDR—were newly launched starting from March 2021. In the context of our research questions and the scope of our paper, it is particularly important to consider only newly issued funds. This ensures direct comparability of initial performance, while maintaining uniform criteria for reporting requirements or the selection of properties to be acquired. Given the introduction of the SFDR in early 2021, a more extensive time series spanning several years is not yet available. The funds have a predominant investment focus on the German property market and are subdivided into core, core plus, value add, and opportunistic according to INREV fund style classifications. As shown in Figure 4.1, the entire sample exhibits a similar risk structure. Only one fund in the sample pursues a value-add investment strategy while the remaining funds range from core to core+. In general, the funds are also homogeneous in terms of size, property type, duration, and investor class, allowing for inter-fund comparisons.

IRR and Bundesverband Investment und Asset Management (BVI) methods serve as performance indicators. The IRR is a money-weighted rate of return that describes the interest rate at which all future or actual cash flows are equal to the initial investments. In the context of real estate funds, the IRR provides insight into the annual capital

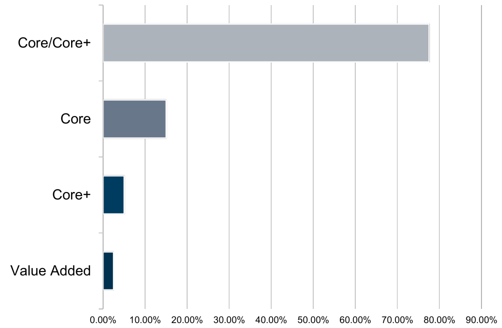


Figure 4.1: Distribution of Investment Styles in % of Total Funds

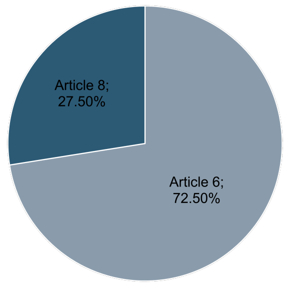


Figure 4.2: Distribution of SFDR Categories in % of Total Funds

return over the total duration of the investment (Hartman & Schafrick, 2004). The BVI-Method is based on the time-weighted rate of return methodology and is used to calculate the performance of investment funds. The performance is the rate of change between the invested capital at the beginning and end of the investment period. To ensure comparability between accumulating and distributing funds, the BVI-method assumes that distributed earnings are immediately reinvested in new fund shares (BVI, 2015).

Both methods have diametrically opposed explanatory power and objectives due to their different methodologies. Timing is a significant factor in the IRR (Hartman & Schafrick, 2004), whereas the BVI is divided into sub-periods, making time a subordinate factor (BVI, 2015). However, since the examined sample consists exclusively of young funds and new acquisitions of properties are regularly made at the beginning of the fund's term, time is a subordinate factor for the sample. In addition, the IRR reflects the actual performance taking into account individual transactions or fees, whereas the BVI represents an objective measure of value and thus ignores transaction costs. However, since the sample examined is made up of funds with a homogeneous cost structure, it is also conceivable to compare the funds using the IRR. Table 4.1 shows the descriptive statistics of the performance indicators. As expected, both performance indicators exhibit similar extreme points and trends.

Regarding the distribution by SFDR category, it is noticeable that most funds do not have any sustainability features (see Figure 4.2). In this context, our sample corresponds to the figures of the BVI, which still show that the majority of funds are of a conventional nature (BVI, 2022). In addition to the previously highlighted key variables such as BVI return, IRR, investment style and SFDR, our dataset includes insights into fund

Table 4.1: Descriptive Statistics

	Internal Rate of Return (IRR)					
SFDR Category	Mean	Median	Q1	Q3	Kurtosis	Skewness
Art. 6	3.73	1.20	0.00	2.81	30.93	2.75
Art. 8	1.80	0.32	-0.06	2.12	8.19	-0.98
	BVI-Method					
Art. 6	-1.40	0.57	-0.10	1.80	19.98	-3.53
Art. 8	1.81	0.00	-0.79	1.67	0.76	1.23

Note: n equals 547 for both IRR and BVI-Method, distributed across a total of 40 funds.

maturity, distinguishing between open-ended and closed-ended structures. Notably, 22.5% of the funds in our sample are closed-ended, while the majority, accounting for 77.5%, adopt an open-ended structure. It is crucial to note that the examined sample comprises specialized alternative investment funds (AIFs) exclusively dedicated to real estate investments and accessible to (semi-)professional investors. In order to be able to estimate coefficients reliably and to depict the relationship between the variables correctly, the dataset is corrected for outliers (Rousseeuw & Leroy, 2005). In the context of our specific dataset and the targeted panel regression, an adjustment for the extreme values is therefore appropriate. For this purpose, we use the methodology of the interquartile range rule adjusted by a multiplier of 2.2 as recommended by Hoaglin and Iglewicz (1987).

4.5 Methodology

J-Curve analysis

To perform the J-Curve analysis in the first section of the paper, the funds' IRR time series are adjusted to $t = 0$ to depict the months following the launch of the funds. The monthly values are then connected using cubic spline interpolation to obtain a smoother curve that captures the trend of the data points. This yields a cubic spline function $S : [a, b] \to \mathbb{R}$ of piecewise third-degree polynomial functions $si(x)$ (Stoer & Bulirsch, 2002).

$$S(x) = \begin{cases} a_1x^3 + b_1x^2 + c_1x + d_1 & \text{if } x \in [x_1, x_2] \\ \dots & \\ a_ix^3 + b_ix^2 + c_ix + d_i & \text{if } x \in [x_{i-1}, x_i] \\ \dots & \\ a_nx^3 + b_nx^2 + c_nx + d_n & \text{if } x \in [x_{n-1}, x_n] \end{cases} \tag{4.1}$$

The polynomial functions (see Equation 8 in the Appendix) are chosen so that they pass through the data points at the ends of each interval, and that they have continuous first and second derivatives at the points at which the intervals intersect (Stoer & Bulirsch, 2002). Regarding endpoint derivatives, De Boor (2001) suggests that the not-a-knot condition approach is preferable to the free-end condition approach. The not-a-knot condition (see Equation 9 in the Appendix) involves selecting values for the end slopes so that the first and last interior nodes are not active. The result of cubic spline interpolation is a smooth curve that passes through the data points and tends to avoid the excessive oscillations commonly associated with high-degree polynomials (Stoer & Bulirsch, 2002). Hence, the method is particularly useful when the dataset is noisy or when there are gaps in the data, as it can provide a reasonable estimate of the underlying function even in these cases. In finance, cubic spline interpolation is a commonly used method, known for its ability to model yield curves, forward curves and other term structures with remarkable accuracy (Holton, 2013). Piecewise integration is applied to determine the negative area under the curve, the so-called "valley of tears", of the early-stage funds' IRR. This involves calculating the integral of the continuous spline function $S(x)$ between $t = 0$ and the break-even point at which $Si(xi) = 0$.

$$\int_a^b S(x)dx = \int_{x_1}^{x_2} s_1(x)dx + \cdots + \int_{x_{1-1}}^{x_i} s_1(x)dx + \cdots + \int_{x_{n-1}}^{x_n} s_n(x)dx \tag{4.2}$$

Panel regression analysis

To assess whether the SFDR category has a significant influence on the overall return of the individual funds, a panel regression is applied. Beyond the conventional pooled OLS model, panel regression analysis offers the flexibility of employing either random or fixed unobserved effects models, addressing potential bias related to omitted variables. These frameworks are commonly applied in related studies to isolate drivers of real estate fund performance (Farrelly & Matysiak, 2012; Fuerst & Matysiak, 2013; Devine et al., 2022). In contrast to the pooled OLS model, the random effects model incorporates a composite error term v_{it} that encompasses a random error component ε_i that is constant over time but differs across observations. The random error term captures the unobserved heterogeneity across observations that is not accounted for by the explanatory variables in the model and is added to the error term of the observations u_{it}. Thus, in the context of our dataset, ε_i also accounts for unobserved fund characteristics such as property type or gearing. The random effects model uses GLS estimation that takes advantage of the serial correlation present in the composite error term.

$$y_{it} = \alpha + \beta x_{it} + v_{it}, \quad v_{it} = \varepsilon_i + u_{it} \tag{4.3}$$

The fixed effects model also controls for time-invariant unobserved heterogeneity with the individual heterogeneity estimated as a parameter. If a time-invariant exogenous variable, such as the SFDR category, is included in the fixed effects model, it does not vary across time and is collinear with the individual fixed effects. As a result, the effects of the time-invariant observables are indistinguishable from the effects of the time-invariant unobservables. Any time-invariant explanatory variable would thus drop from the fixed effects model. Due to this drawback of the fixed effects model when including binary variables, it is not considered appropriate for the present analysis (Wooldridge, 2002). This is further confirmed by high p-values in the Hausman test (see Table 4.5).

To ensure efficient estimation within the GLS framework, additional assumptions are required that go beyond the OLS model. The Appendix provides a detailed overview of the model specification tests. Specifically, the tests proposed by Baltagi (2021) are presented in more detail to identify potential advantages of a random effects model over a fixed effects model and pooled OLS. This includes the examination of the Hausman test and the T. Breusch and Pagan (1980) Lagrange multiplier (LM) test. Furthermore, the Appendix encompasses the panel diagnostic tests conducted.

4.6 Empirical Results and Implications

J-Curve analysis

Since the funds in our dataset were launched with the introduction of the SFDR at the beginning of 2021 and are therefore considered immature, we examine their initial return characteristics in more detail. Private equity or unlisted real estate funds typically exhibit high upfront costs related to fund administration, marketing, property acquisition, and management fees, which tend to impact the short-term IRR. These costs accumulate until sufficient fund inflows are generated to begin the investment phase. Moreover, investment managers do not immediately draw down investors' money upon launching the fund but rather gradually as the properties are acquired. Accordingly, investors are not invested in real estate but continue to be invested in cash for the time being. Both factors translate into a negative initial performance of unlisted real estate funds. As soon as the first properties are acquired and the cash flow stabilizes, the initially negative returns are amortized, and hence the so-called J-Curve emerges. Analyzing the funds' J-Curve can provide diverse insight into key figures, such as break-even point or risk of default (Diller et al., 2009). In the context of the SFDR, the question arises as to whether a J-Curve pattern can be discerned in the present dataset and whether this is more pronounced for Article 8 funds. A priori, one may assume that the upfront costs for Article 8 or 9 funds are higher than for Article 6 funds. More extensive due diligence for identifying suitable properties could lead to an increase in funds' upfront costs and further delay the drawdown of investors' capital. In addition, funds categorized under the SFDR must comply with article-specific requirements and disclose how sustainable features, risks and objectives are considered in the respective investment strategy. This implies additional expenses in the elaboration and preparation of the fund documentation, which is also subject to a separate review by the capital investment company. Finally, the reporting continuously monitors compliance with the respective SFDR category. Fundraising, documentation, property acquisition and reporting, therefore, might result in additional costs both before the launch of the fund and after the allocation of investors' money. This might contribute to a more pronounced J-Curve for Article 8 funds.

To investigate this relationship further, the IRR time series of the dataset were plotted as months after fund launch, using cubic spline interpolation. The equation of the cubic spline interpolation for both J-Curves is provided in the Appendix. As Figure 4.3 illustrates, the funds' IRR exhibits a J-Curve pattern as anticipated, regardless of the SFDR category. The analysis reveals that the break-even point of the J-Curve, i.e., the point at which the IRR turns positive is reached approximately 0.53 months earlier for Article 8 funds. This observation becomes especially clear in the direct comparison of the curves in Figure 4.4. To determine the negative area of the J-Curve, which is often referred to as the so-called valley of tears, the piecewise integrals of the spline functions are applied. The break-even point of the IRR and the starting point of the time series are defined as the upper and lower limits of the integrals, respectively. Figure 4.5 highlights the valley of tears for both SFDR categories. The results of the integrals show that Article 8 funds have a less pronounced negative area of the J-Curve, which is at odds with the previously assumed impact of the SFDR category on the initial IRR:

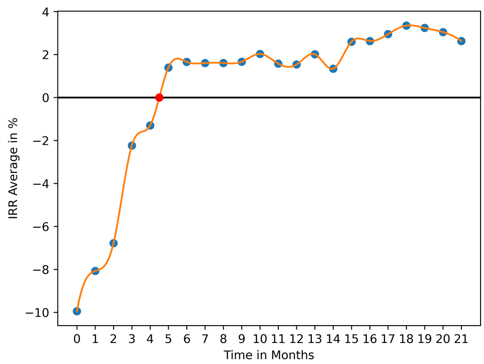
$$\int_0^{4,50} S(x)\,dx = -22.81 \tag{4.4}$$

Integral Article 6

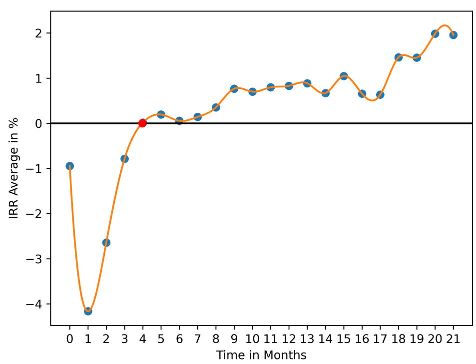
$$\int_0^{3,97} S(x)\,dx = -8.70 \tag{4.5}$$

Integral Article 8

Since the dataset does not provide any information on the actual cost structures of the respective funds, no analysis can be carried out in this regard. However, the results allow for the conclusion that either the funds' upfront costs do not depend on the respective SFDR category, or that initially higher costs are amortized more quickly after the funds' cash flow stabilizes. The fund category under Article 8, therefore, does not entail any disadvantages regarding the initial IRR. To conduct a more in-depth analysis of the impact of the SFDR categories on funds' overall returns, a panel regression analysis is carried out.



(a) Article 6 J-Curve



(b) Article 8 J-Curve

Figure 4.3: Comparison of J-Curves

Panel regression

Our analysis comprises a total of four different individual random effects models, consisting of two base models and two extensions thereof. In our base models (Model 1a and 1b), the dependent variable y is defined by the return metrics IRR and BVI. The control variables of the panel regression models are represented by the funds' investment style and whether the funds are open- or closed-ended. Furthermore, a lagged return variable $y(t-1)$ is included to improve model accuracy (Farrelly & Matysiak, 2012; Fuerst & Matysiak, 2013). Relevant for answering the research question is the independent dummy variable "SFDR", in which $0 = \textit{Article}\ 6$ and $1 = \textit{Article}\ 8$. Investment style is a factor variable in which $0 = \textit{Core}$ and the Open-/Closed-Ended variable is denoted as $\textit{Closed} - \textit{Ended} = 0$. In models 2a) and 2b), model accuracy is to be improved by adding external economic factors which may correlate with returns. GDP growth is typically considered to be a significant factor contributing to rental and value growth in the real estate market. However, GDP data is updated on a quarterly basis and can thus not be included as an explanatory variable in the present monthly

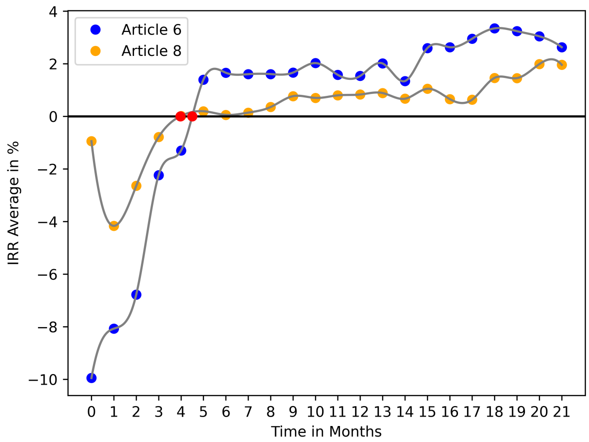
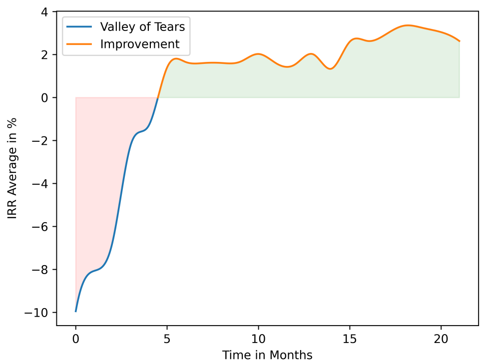
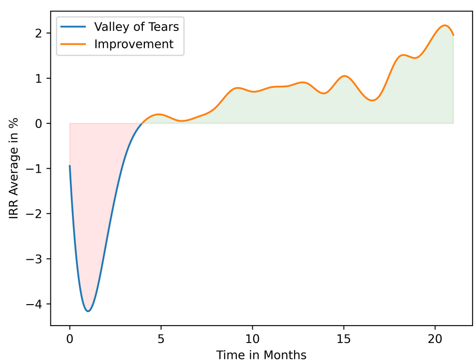


Figure 4.4: Superimposed J-Curves



(a) Article 6 J-Curve



(b) Article 8 J-Curve

Figure 4.5: Comparison of J-Curves with Valley of Tears

panel data analysis. Instead, the term spread between the German 10-year government bond yield and the 3-month yield is used (Federal Reserve Bank of St. Louis, 2023). The yield curve has predictive capabilities that go beyond the growth in economic activity and short-term interest rates, making it a valuable leading indicator for economic output and recessions (Estrella & Hardouvelis, 1991; Estrella et al., 2000; Chinn & Kucko, 2015). This sensitivity to the term structure of interest rates can also observed within the real estate context (Akimov et al., 2015). In addition to interest rates, which are endogenously determined by monetary policy, the exogenous availability and cost of debt capital can have an impact on the performance of real estate investments. For this reason, the relative change in credit margins for average loans to businesses is included as an independent variable (Deutsche Bundesbank, 2023). The movements in banks' terms and conditions for loans indicate the perception of risk in the lending sector.

The results of the model specification tests strongly suggest the use of individual random effects in both IRR and BVI models. The LM test yields p-values of 0.0000 in both cases, providing substantial evidence against the null hypothesis of the pooled OLS model. This implies that the random effects model is a more suitable choice. Additionally, the Hausman test with p-values of 0.9343 (IRR) and 0.7731 (BVI) fails to reject the null hypothesis of systematic differences between random and fixed effects, further reinforcing the choice of random effects. Subsequently, we examine whether there is a systematic change in the statistical properties of the IRR and BVI series. The low p-values of the unit root tests in Table 4.2 provide strong evidence against the presence of a unit root and hence support stationarity for both series. Regardless of the assumption of cross-sectional dependence, the results are unambiguous for both types of test. Only in the inverse normal Fisher-type test, the p-value for BVI is slightly above the significance level of 0.05 yet still under the 0.10 significance level. Regarding serial correlation, the results of the Wooldridge test align with expectations based on the relatively short time series. With p-values of 0.6345 (IRR) and 0.1599 (BVI), the null hypothesis of no serial correlation is not rejected. As the Breusch–Pagan test indicates the presence of heteroskedasticity in the models, it is corrected for by using a heteroskedasticity-consistent covariance estimation as suggested by Zeileis (2004). Given the absence of serial correlation in the models, robust standard errors are employed instead of heteroskedasticity- and autocorrelation-consistent clustered standard errors. While in time series data the information criteria AIC and BIC are applied to determine the optimal lag length, panel data analysis commonly relies on economic theory and alternative measures such as adjusted R^2 to determine the appropriate lag length. Accordingly, the lag length for both term and loan spread in models 2a) and 2b) is set at three months.

Table 4.2: Panel Unit Root Tests

	IRR	**BVI**
Cross-sectional independence		
Fisher-type: Inverse Chi-square	155.25 (0.0000)	147.52 (0.0000)
Fisher-type: Inverse Normal	-2.9103 (0.0018)	-1.2823 (0.0999)
Fisher-type: Logit	-4.4705 (0.0000)	-2.0939 (0.0188)
Cross-sectional dependencies		
Pesaran Panel Unit Root Test	-2.0167 (0.0100)	-2.0586 (0.0100)

Note: p-values are presented in parentheses.
Sample sizes: 437 (38 funds) for IRR and 434 (36 funds) for BVI.

The results of models 1a) and 1b) can be seen in Table 4.3. The SFDR Article 8 variable has a significant influence on both the IRR and the BVI return, with p-values smaller than 0.05 and 0.01, respectively. In contrast to the initial J-Curve analysis which suggests a performance premium for Article 8 funds up to the funds' break-even point, the results of the regression analysis indicate that Article 8 funds perform slightly worse than their Article 6 peers when the overall time series is considered. When controlling for differences in fund characteristics, the inclusion of the Article 8 dummy leads to a decrease in returns of about 0.5% points in both models. We attribute the minimal difference in results between IRR and BVI to the fact that the distinct methodologies of money-weighted and time-weighted returns, as explained earlier, have little impact due to the homogeneity and relative young vintage year of the funds under consideration. This pattern of returns for Article 8 funds is further supported by an eyeball test of the figures in the J-Curve analysis. Toward the end of the time series, the monthly IRR values for Article 8 funds consistently fall below the values of Article 6 funds.

One possible explanation for this observation is that Article 8 funds tend to offer a more conservative risk-return profile. The enhanced sustainability standards applied to Article 8 funds, along with the availability of more comprehensive data for reporting, can contribute to improved risk management capabilities. At the same time, Article 8 funds tend to acquire newer properties which meet the sustainability standards and thus exhibit less property-related risks. However, it should be noted that the analyzed

Table 4.3: Random Effects Model 1a) and Model 1b)

	IRR					BVI				
Coefficients	Estimate	Std. Error	Z-Value	Prob.		Estimate	Std. Error	Z-Value	Prob.	
(Intercept)	1.4146	0.4710	3.0032	0.0028	**	0.6140	0.2391	2.5683	0.0106	*
Core/Core+	-0.8140	0.3864	-2.1064	0.0357	*	-0.4444	0.2148	-2.0683	0.0392	*
Core+	1.1710	0.5996	1.9531	0.0515	.	1.1918	0.4892	2.4362	0.0153	*
Value Added	-0.8201	1.7453	-0.4699	0.6387		0.0371	0.6481	0.0573	0.9543	
Art. 8	-0.5026	0.2218	-2.2658	0.0240	*	-0.4873	0.1425	-3.4192	0.0007	***
Open Ended	0.1767	0.2334	0.7569	0.4495		0.4509	0.1491	3.0239	0.0026	**
y (t-1)	0.4475	0.1415	3.1626	0.0017	**	0.5338	0.0660	8.0818	0.0000	***
TSS	974.46					730.81				
RSS	379.31					203.39				
R-Squared	0.6108					0.7217				
Adj. R-Squared	0.6054					0.7178				
Chi-squared	668.41					1095.44				
Funds	38					36				
T-Max	21					21				
Sample size (n)	437					434				

Note: The significance levels are indicated as follows: $^{***} = p < 0.001$, $^{**} = p < 0.01$, $^{*} = p < 0.05$, $\cdot = p < 0.1$.

time series represents only the initial period of the funds, i.e., the time when the first assets were being acquired. Hence, we assume that (default) risks are not realized to the extent that they would be perceptible in calculations of IRR or BVI. Although the dataset is corrected for outliers, the return metrics are also strongly influenced by initial property acquisitions and irregular cash flows. Consequently, both factors imply that Article 8 funds may be subject to a temporal bias, which could adversely affect the reported returns. Despite the absence of existing literature on SFDR and unlisted real estate returns, which limits our ability to interpret our findings, we can still draw parallels with relevant studies.

Our results can be aligned with the observations made by Devine et al. (2022), who found that voluntary sustainability reporting through GRESB does not confer advantages on funds' income component of total returns but rather affects the capital component. Given the brevity of our time series, it is unlikely that realized capital gains are already reflected in our return series. In a more comprehensive perspective, our observations also correspond to the findings presented by Cajias et al. (2014), which suggest that, whereas share prices incorporate ESG changes contemporaneously, the tangible effects on business operations exhibit a time lag. The authors note that negative ESG scores are associated with higher short-term returns whereas a positive impact of

ESG factors might tend to manifest more prominently in the long run. As such, both in the context of the implied risk pricing and the capital growth of the funds' underlying properties, our study lacks a longer time series to make conclusive statements about the long-term impact of the SFDR category on fund returns. When considering the results in the context of the regulatory requirements outlined in the SFDR, it is essential to address the potential influence of evolving reporting requirements on performance. The underlying dataset does not provide a breakdown of individual indicators (such as the classification of properties within the framework of the minimum "Do No Harm" indicators) but rather assumes a holistic approach encompassing all indicators. Brounen and van der Spek (2023) demonstrate that the voluntary GRESB Total Score does not have a significant impact on value, whereas an examination of individual scores can indeed influence value. Hence, it is conceivable that a more nuanced analysis within the context of the SFDR and unlisted real estate funds could offer further insights.

Regarding the remaining independent variables, it is noteworthy that, contrary to initial expectations, there is no observed performance advantage for core/core+ funds compared to pure core funds. Instead, core/core+ funds appear to exert a significant negative impact on performance. This outcome can be attributed to the nuanced categorization of these funds, which seems to blur the distinction between core and core+ strategies. On the other hand, a distinct premium of approximately 1.2% points is observed for pure core+ funds in comparison to core funds. With regard to the BVI, open-ended funds demonstrate a premium of 0.45% points compared to closed-ended funds. One possible explanation for this observation could be that closed-ended funds inherently place a stronger emphasis on the capital component, as their investment horizon is predetermined from the outset, in contrast to open-ended funds. However, as previously explained, our time series is expected to demonstrate minimal to nonexistent positive influence from the capital component, with the emphasis primarily placed on the income component. The ambiguous influences of the fund characteristics across models can also be attributed to the fact, as already noted by Stevenson (2006), that, in the case of very young funds, the specified fund objectives such as leverage, diversification, or investment volume may not have been fully realized yet. The inclusion of the lagged return variable $y(t-1)$ proves to be applicable, as indicated by the positive and statistically significant results.

The outcomes of models 2a) and 2b) presented in Table 4.4 provide complete affirmation of the findings obtained from the previous models. While the market variables we have highlighted can potentially serve as leading indicators for predicting returns of unlisted real estate funds, the inclusion of external variables does not offer any new revelations. This observation can be attributed to the relatively new launch of the

Table 4.4: Random Effects Model 2a) and Model 2b)

	IRR					BVI				
Coefficients	Estimate	Std. Error	Z-Value	Prob.		Estimate	Std. Error	Z-Value	Prob.	
(Intercept)	1.3050	0.4821	2.7070	0.0071	**	0.5143	0.2898	1.7749	0.0766	.
Core/Core+	-0.8286	0.3988	-2.0780	0.0383	*	-0.4516	0.2276	-1.9839	0.0479	*
Core+	1.0831	0.6051	1.7900	0.0742	.	1.1406	0.5132	2.2225	0.0268	*
Value Added	-1.0369	1.7592	-0.5894	0.5559		-0.0977	0.6414	-0.1524	0.8790	
Art. 8	-0.5374	0.2354	-2.2832	0.0229	*	-0.5232	0.1485	-3.5242	0.0005	***
Open Ended	0.1659	0.2333	0.7112	0.4773		0.4666	0.1531	3.0476	0.0025	**
y (t-1)	0.4252	0.1471	2.8910	0.0040	**	0.5072	0.0662	7.6670	0.0000	***
Term Spread (t-3)	9.0415	14.6195	0.6185	0.5366		6.8916	13.6005	0.5067	0.6126	
Loan Spread (t-3)	8.6171	6.0201	1.4314	0.1531		6.3647	4.0149	1.5853	0.1136	
TSS	950.65					691.71				
RSS	366.58					194.33				
R-Squared	0.6145					0.7191				
Adj. R-Squared	0.6073					0.7138				
Chi-squared	674.61					1074.23				
Funds	38					36				
T-Max	21					21				
Sample size (n)	437					434				

Note: The significance levels are indicated as follows: $^{***} = p < 0.001$, $^{**} = p < 0.01$, $^{*} = p < 0.05$, $^{\cdot} = p < 0.1$.

funds, with returns primarily influenced by property acquisition and volatile cash flows rather than the overall economy or financing conditions. This supposition is also reflected in the adjusted R^2, which shows no significant increase. The fact that external economic variables do not appear significant aligns with the findings of Devine et al. (2022), which suggest that the impact of GRESB scores is independent of local economic conditions. In our case, we attribute this phenomenon firstly to the reaction time of market participants, as indicated by our comparatively short time series. Secondly, we ascribe this to the long-term investment horizon of our sample, which is less dependent on local economic conditions in the short term. Regarding the SFDR category, Article 8 funds exhibit a slightly greater adverse impact on performance. Overall, the results obtained remain consistent.

Beyond the purely financial perspective, it is valuable to examine the tangible effectiveness of the SFDR for sustainable investment strategies. While there is some evidence that increased sustainability transparency is encouraging investment funds to raise their ESG ambitions, the SFDR is falling somewhat short of its intended purpose, particularly in the area of non-listed real estate investments (Becker et al., 2022; Ferriani, 2023).

INREV not only published a comprehensive document outlining the shortcomings of the SFDR but also submitted a response to the European Commission's SFDR consultation in December 2023, highlighting the key weaknesses of the SFDR in the real estate asset class (INREV, 2023; INREV, 2023). A key concern in the documents is the difficulty of applying SFDR to non-static asset classes such as real estate. Real estate investments involve a business strategy that is executed over an extended investment horizon. This is particularly evident in sustainable real estate investment products, which focus on transition strategies of property portfolios. Transition strategies involve retrofitting older buildings to enhance energy efficiency, phasing out on-site fossil fuel combustion, and installing on-site renewable energy systems. The implementation of these measures requires integration into the funds' CapEx planning to ensure an optimal balance between environmental payback (trade-off between embodied and operational carbon) and economic payback (trade-off between CapEx and operational savings). Of particular importance in supporting funds' transition strategies is the reallocation of capital. While the SFDR is intended to shift capital to more sustainable investments, a large proportion of older and inefficient properties is held in Article 6 funds. With Article 8 funds as a minimum requirement for many investors and banks, there is a risk that capital will not be made available for the transformation of the existing, inefficient property stock. Furthermore, as noted by Cremasco and Boni (2022) and INREV (2023), there is a risk of greenwashing when the categories of the SFDR are rigidly perceived as green labels, with Article 8 being categorized as light green and Article 9 as deep green. However, these categories do not guarantee actual sustainability performance. Hence, to ensure effective risk management, it is necessary to evaluate not only the SFDR category of a fund but also its business plan and sustainability objectives. It is important to note that the SFDR is a dynamic framework that is subject to continuous changes, particularly in response to pressures from various associations and initiatives. Investment decisions based solely on the SFDR category can turn into risk positions in case of possible changes in the SFDR labeling regime.

4.7 Conclusions

The results of the present study indicate that Article 8 funds do not significantly underperform Article 6 funds in the initial phase after launch. On the contrary, Article 8 funds achieve positive returns even before their Article 6 peers. As typical for unlisted funds, the development of the funds' IRR in our dataset follows a J-Curve pattern over time. A priori, we assumed that Article 8 funds, especially in the initial phase, would exhibit a more pronounced J-Curve with longer periods of negative returns. However, the results of the J-Curve analysis refute this hypothesis. This may reflect either that the initial costs of the funds are not affected by the SFDR category or that the higher initial costs are recovered more quickly, for example by attracting more investors and hence generating more fund inflows. The results of the panel regression analysis confirm, across models, that the SFDR category has a significant influence on both the IRR and BVI returns. In contrast to the examination of funds' J-Curve, the models in the panel regression analysis show that Article 8 funds perform slightly worse than their Article 6 peers when considered over the entire period. This can be attributed to several potential factors. We assume that properties eligible for Article 8 SFDR have a more conservative risk-return profile as they tend to be newer and more sustainable properties. The availability of comprehensive data required for SFDR reporting will, in any case, enable better risk management at the fund level. Article 8 funds may exhibit a more conservative risk-return profile, resulting in lower returns. Additionally, any incremental capital gains may materialize with a time lag and become apparent in the long run. Finally, it is possible that some risks related to the properties have not been fully captured in the IRR or BVI return figures yet, and the returns themselves may be biased due to property acquisitions and volatile cash flows at the initial stage of the funds. As real estate funds typically have a long-term investment horizon, this paper serves as a foundation for further research. Future analysis could provide valuable insights into the impact of SFDR disclosure on non-listed real estate funds, in particular whether the SFDR has a systematic impact on financial markets within the EU compared to other markets where no regulatory action has been taken. Current evidence from the industry suggests that the SFDR falls short of its objective with regard to unlisted real estate. It remains to be seen to what extent policymakers will accelerate the decarbonization of the property sector through targeted regulation. Real estate stakeholders should prepare for dynamically changing regulatory conditions and continue to monitor a broad range of sustainability KPIs to meet future market requirements.

4.8 Appendix

The following equation reflects the cubic spline for Article 6 funds:

$$s(x) = \begin{cases} 1.2970 \cdot x^3 - 8.0726 \cdot x^2 + 1.7016 \cdot 10^1 \cdot x - 2.0192 \cdot 10^1, & \text{if } x \in [1,2], \\ 1.2970 \cdot x^3 - 8.0726 \cdot x^2 + 1.7016 \cdot 10^1 \cdot x - 2.0192 \cdot 10^1, & \text{if } x \in (2,3], \\ -2.6593 \cdot x^3 + 2.7534 \cdot 10^1 \cdot x^2 - 8.9805 \cdot 10^1 \cdot x + 8.6629 \cdot 10^1, & \text{if } x \in (3,4], \\ 2.4899 \cdot x^3 - 3.4256 \cdot 10^1 \cdot x^2 + 1.5736 \cdot 10^2 \cdot x - 2.4292 \cdot 10^2, & \text{if } x \in (4,5], \\ -1.9344 \cdot x^3 + 3.2108 \cdot 10^1 \cdot x^2 - 1.7446 \cdot 10^2 \cdot x + 3.1011 \cdot 10^2, & \text{if } x \in (5,6], \\ 1.0549 \cdot x^3 - 2.1699 \cdot 10^1 \cdot x^2 + 1.4838 \cdot 10^2 \cdot x - 3.3557 \cdot 10^2, & \text{if } x \in (6,7], \\ -1.7048 \cdot 10^{-1} \cdot x^3 + 4.0341 \cdot x^2 - 3.1754 \cdot 10^1 \cdot x + 8.4739 \cdot 10^1, & \text{if } x \in (7,8], \\ 6.1301 \cdot 10^{-4} \cdot x^3 - 7.2122 \cdot 10^{-2} \cdot x^2 + 1.0957 \cdot x - 2.8596, & \text{if } x \in (8,9], \\ 1.6596 \cdot 10^{-1} \cdot x^3 - 4.5366 \cdot x^2 + 4.1276 \cdot 10^1 \cdot x - 1.2340 \cdot 10^2, & \text{if } x \in (9,10], \\ -4.1380 \cdot 10^{-1} \cdot x^3 + 1.2856 \cdot 10^1 \cdot x^2 - 1.3265 \cdot 10^2 \cdot x + 4.5636 \cdot 10^2, & \text{if } x \in (10,11], \\ 3.7522 \cdot 10^{-1} \cdot x^3 - 1.3181 \cdot 10^1 \cdot x^2 + 1.5376 \cdot 10^2 \cdot x - 5.9382 \cdot 10^2, & \text{if } x \in (11,12], \\ 1.2648 \cdot 10^{-1} \cdot x^3 - 4.2267 \cdot x^2 + 4.6306 \cdot 10^1 \cdot x - 1.6400 \cdot 10^2, & \text{if } x \in (12,13], \\ -7.6730 \cdot 10^{-1} \cdot x^3 + 3.0631 \cdot 10^1 \cdot x^2 - 4.0684 \cdot 10^2 \cdot x + 1.7996 \cdot 10^3, & \text{if } x \in (13,14], \\ 1.2809 \cdot x^3 - 5.5394 \cdot 10^1 \cdot x^2 + 7.9751 \cdot 10^2 \cdot x - 3.8207 \cdot 10^3, & \text{if } x \in (14,15], \\ -1.2926 \cdot x^3 + 6.0415 \cdot 10^1 \cdot x^2 - 9.3963 \cdot 10^2 \cdot x + 4.8650 \cdot 10^3, & \text{if } x \in (15,16], \\ 7.5240 \cdot 10^{-1} \cdot x^3 - 3.7746 \cdot 10^1 \cdot x^2 + 6.3095 \cdot 10^2 \cdot x - 3.5114 \cdot 10^3, & \text{if } x \in (16,17], \\ -2.1142 \cdot 10^{-1} \cdot x^3 + 1.1409 \cdot 10^1 \cdot x^2 - 2.0468 \cdot 10^2 \cdot x + 1.2239 \cdot 10^3, & \text{if } x \in (17,18], \\ -1.2627 \cdot 10^{-1} \cdot x^3 + 6.8103 \cdot x^2 - 1.2191 \cdot 10^2 \cdot x + 7.2723 \cdot 10^2, & \text{if } x \in (18,19], \\ 1.4802 \cdot 10^{-1} \cdot x^3 - 8.8241 \cdot x^2 + 1.7514 \cdot 10^2 \cdot x - 1.1541 \cdot 10^3, & \text{if } x \in (19,20], \\ -5.5360 \cdot 10^{-2} \cdot x^3 + 3.3788 \cdot x^2 - 6.8917 \cdot 10^1 \cdot x + 4.7295 \cdot 10^2, & \text{if } x \in (20,21], \\ -5.5360 \cdot 10^{-2} \cdot x^3 + 3.3788 \cdot x^2 - 6.8917 \cdot 10^1 \cdot x + 4.7295 \cdot 10^2, & \text{if } x \in (21,22]. \end{cases} \tag{4.6}$$

Table 4.5: Hausman Tests

Hausman tests	**IRR**	**BVI**
Chi-Square	0.8304	1.7966
	(0.9343)	(0.7731)
Degrees of Freedom	4	4

Note: p-values are presented in parentheses.
Sample sizes: 437 (38 funds) for IRR and 434 (36 funds) for BVI.

The following equation reflects the cubic spline for Article 8 funds:

$$s(x) = \begin{cases} -8.4637 \cdot 10^{-1} \cdot x^3 + 7.4483 \cdot x^2 - 1.9639 \cdot 10^1 \cdot x + 1.2091 \cdot 10^1, & \text{if } x \in [1,2], \\ -8.4637 \cdot 10^{-1} \cdot x^3 + 7.4483 \cdot x^2 - 1.9639 \cdot 10^1 \cdot x + 1.2091 \cdot 10^1, & \text{if } x \in (2,3], \\ -1.7337 \cdot 10^{-1} \cdot x^3 + 1.3913 \cdot x^2 - 1.4681 \cdot x - 6.0802, & \text{if } x \in (3,4], \\ 1.5093 \cdot 10^{-1} \cdot x^3 - 2.5003 \cdot x^2 + 1.4098 \cdot 10^1 \cdot x - 2.6835 \cdot 10^1, & \text{if } x \in (4,5], \\ -7.4049 \cdot 10^{-4} \cdot x^3 - 2.2521 \cdot 10^{-1} \cdot x^2 + 2.7230 \cdot x - 7.8765, & \text{if } x \in (5,6], \\ 1.5888 \cdot 10^{-1} \cdot x^3 - 3.0983 \cdot x^2 + 1.9962 \cdot 10^1 \cdot x - 4.2354 \cdot 10^1, & \text{if } x \in (6,7], \\ -9.1780 \cdot 10^{-2} \cdot x^3 + 2.1655 \cdot x^2 - 1.6885 \cdot 10^1 \cdot x + 4.3622 \cdot 10^1, & \text{if } x \in (7,8], \\ 1.0800 \cdot 10^{-1} \cdot x^3 - 2.6292 \cdot x^2 + 2.1473 \cdot 10^1 \cdot x - 5.8665 \cdot 10^1, & \text{if } x \in (8,9], \\ -2.6341 \cdot 10^{-1} \cdot x^3 + 7.3988 \cdot x^2 - 6.8780 \cdot 10^1 \cdot x + 2.1209 \cdot 10^2, & \text{if } x \in (9,10], \\ 2.6395 \cdot 10^{-1} \cdot x^3 - 8.4219 \cdot x^2 + 8.9427 \cdot 10^1 \cdot x - 3.1526 \cdot 10^2, & \text{if } x \in (10,11], \\ -1.5044 \cdot 10^{-1} \cdot x^3 + 5.2529 \cdot x^2 - 6.0995 \cdot 10^1 \cdot x + 2.3628 \cdot 10^2, & \text{if } x \in (11,12], \\ 1.1076 \cdot 10^{-1} \cdot x^3 - 4.1502 \cdot x^2 + 5.1842 \cdot 10^1 \cdot x - 2.1506 \cdot 10^2, & \text{if } x \in (12,13], \\ -2.0266 \cdot 10^{-1} \cdot x^3 + 8.0732 \cdot x^2 - 1.0706 \cdot 10^2 \cdot x + 4.7352 \cdot 10^2, & \text{if } x \in (13,14], \\ 4.0108 \cdot 10^{-1} \cdot x^3 - 1.7284 \cdot 10^1 \cdot x^2 + 2.4794 \cdot 10^2 \cdot x - 1.1832 \cdot 10^3, & \text{if } x \in (14,15], \\ -5.3434 \cdot 10^{-1} \cdot x^3 + 2.4810 \cdot 10^1 \cdot x^2 - 3.8347 \cdot 10^2 \cdot x + 1.9739 \cdot 10^3, & \text{if } x \in (15,16], \\ 3.7377 \cdot 10^{-1} \cdot x^3 - 1.8779 \cdot 10^1 \cdot x^2 + 3.1396 \cdot 10^2 \cdot x - 1.7457 \cdot 10^3, & \text{if } x \in (16,17], \\ 1.7844 \cdot 10^{-1} \cdot x^3 - 8.8178 \cdot x^2 + 1.4461 \cdot 10^2 \cdot x - 7.8609 \cdot 10^2, & \text{if } x \in (17,18], \\ -6.1010 \cdot 10^{-1} \cdot x^3 + 3.3764 \cdot 10^1 \cdot x^2 - 6.2186 \cdot 10^2 \cdot x + 3.8127 \cdot 10^3, & \text{if } x \in (18,19], \\ 5.8007 \cdot 10^{-1} \cdot x^3 - 3.4076 \cdot 10^1 \cdot x^2 + 6.6710 \cdot 10^2 \cdot x - 4.3506 \cdot 10^3, & \text{if } x \in (19,20], \\ -3.3612 \cdot 10^{-1} \cdot x^3 + 2.0896 \cdot 10^1 \cdot x^2 - 4.3233 \cdot 10^2 \cdot x + 2.9789 \cdot 10^3, & \text{if } x \in (20,21], \\ -3.3612 \cdot 10^{-1} \cdot x^3 + 2.0896 \cdot 10^1 \cdot x^2 - 4.3233 \cdot 10^2 \cdot x + 2.9789 \cdot 10^3, & \text{if } x \in (21,22]. \end{cases} \tag{4.7}$$

Table 4.6: Breusch-Pagan Tests for Lagrange Multiplier and Heteroscedasticity

Test Type	**IRR**	**BVI**
Lagrange Multiplier Test		
Chi-Square	142.00	51.99
	(0.0000)	(0.0000)
Degrees of Freedom	1	1
Heteroscedasticity Test		
BP	13.29	472.46
	(0.0041)	(0.0000)
Degrees of Freedom	3	3

Note: *p*-values are presented in parentheses.
Sample sizes: 437 (38 funds) for IRR and 434 (36 funds) for BVI.

Table 4.7: Wooldridge Test

Wooldridge tests	**IRR**	**BVI**
F	0.2263	1.9815
	(0.6345)	(0.1599)
Degrees of Freedom	1	1

Note: *p*-values are presented in parentheses.
Sample sizes: 437 (38 funds) for IRR and 434 (36 funds) for BVI.

Cubic Spline Interpolation: Intersection Condition.

$$
\begin{gathered}
s_i\left(x_{i-1}\right)=y_{i-1}, s_i\left(x_i\right)=y_i \\
\frac{d^1}{d x^1} s_{i-1}\left(x_i\right)=\frac{d^1}{d x^1} s_i\left(x_i\right), \quad \frac{d^2}{d x^2} s_{i-1}\left(x_i\right)=\frac{d^2}{d x^2} s_i\left(x_i\right)
\end{gathered} \tag{4.8}
$$

Cubic Spline Interpolation: Not-a-Knot Condition.

$$
\begin{gathered}
\frac{d^3}{d x^3} s_1\left(x_1\right)=\frac{d^3}{d x^3} s_2\left(x_2\right) \quad \mid x_1=x_2 \\
\frac{d^3}{d x^3} s_{n-1}\left(x_{n-1}\right)=\frac{d^3}{d x^3} s_n\left(x_n\right) \mid x_{n-1}=x_n
\end{gathered} \tag{4.9}
$$

Model selection and panel diagnostics:
Under the strict exogeneity assumption of the GLS framework the composite error term is random and uncorrelated with the explanatory variables $E(v_{it}/x_{it})=0$. Furthermore, it is assumed that the idiosyncratic errors u_{it} have a constant and unconditional variance $E(u_{it}^2)=\sigma_u^2$ and exhibit no autocorrelation among different observations $E(u_{it}/u_{is})=0$ (Wooldridge, 2002). Baltagi (2021) suggests employing the Hausman test statistic, which incorporates the assumption $E(v_{it}/x_{it})=0$, to ascertain whether the GLS estimator $\hat{\beta}_{GLS}$ of the random effects model is consistent and efficient compared to the estimator of the within transformation of the fixed effects model $\hat{\beta}_{Within}$. It has the null hypothesis of no systematic difference between the estimates obtained from both random and fixed effects model. The test statistic follows an asymptotical distribution χ_K^2 with K being a measure for the dimension of the slope vector β.

$$
m_1=\hat{q}_1^{\prime}\left[\operatorname{var}\left(\hat{q}_1\right)\right]^{-1} \hat{q}_1, \quad \hat{q}_1=\hat{\beta}_{GLS}-\hat{\beta}_{within} \tag{4.10}
$$

The T. Breusch and Pagan (1980) LM test as proposed by Baltagi (2021) is applied to determine the presence of random effects in the model establishing the suitability of either a random effects model or a pooled ordinary least squares model. Under the null hypothesis of no effects, the variance of the random effect σ_ε^2 is zero. The LM test statistic is asymptotically distributed as χ^2 with $\hat{u}_{it}$ as the residual of the pooled ordinary least squares model.

$$
LM=\frac{NT}{2(T-1)}\left[\frac{\sum_{i=1}^N\left(\sum_{t=1}^T \hat{u}_{it}\right)^2}{\sum_{i=1}^N \sum_{t=1}^T \hat{u}_{it}^2}-1\right]^2 \tag{4.11}
$$

T. S. Breusch and Pagan (1979) developed another test based on the Lagrange multiplier which is used to detect heteroscedasticity in the model and, therefore, a change in the variance of the residuals. It has the null hypothesis of homoskedasticity and is asymptotically distributed as χ^2. According to T. S. Breusch and Pagan (1979), using an auxiliary regression with $g_t = \hat{\sigma}^2 \hat{u}_t^2$ where $\hat{\sigma}^2 = N^{-1} \sum \hat{u}_t^2$, the LM test statistic can be determined as $2^{-1}ESS$.

Serial correlation is another issue that may cause the regression results to be biased. Although panel datasets with short time series are less prone to serial correlation, the Wooldridge (2002) first-difference test as suggested by Drukker (2003) is applied. It is a straight-forward test for unbalanced panels in both fixed and random effects one-way models with the null hypothesis of no serial correlation in the idiosyncratic errors.

A fundamental assumption in panel regression analysis is the stationarity of the underlying data over time, characterized by the absence of a unit root. As a result, the statistical properties of the data, including the mean, variance and autocorrelation, are presumed to remain constant throughout the observation period. According to Maddala and Wu (1999) and Choi (2001), the Fisher-type test is a superior alternative to the panel unit root tests by Levin-Lin (LL) and Im-Pesaran-Shin (IPS). Unlike the IPS test, the Fisher-type test can be applied to unbalanced panels. The Fisher-type test combines the p-values p_i of N independent unit root tests. It assumes that all series under the null are non-stationary based on the p-values of the individual unit root tests, while the alternative is that at least one series in the panel is stationary. As proposed by Choi (2001), three versions of the Fisher-type test based on the inverse chi-square, inverse normal and logit test are performed in this paper. While the inverse chi-square and inverse normal test statistics have an exact asymptotic distribution, the logit test statistic follows an approximated asymptotic distribution.

$$
\begin{aligned}
&P = -2 \sum_{i=1}^{N} \ln (p_i) \sim \chi_N^2, \quad Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1} (p_i) \sim N(0,1), \\
&L = \sum_{i=1}^{N} \ln \left(\frac{p_i}{1-p_i} \right) \text{ with } L^* = \sqrt{k} L \Rightarrow t_{5N+4} \text{ where } k = \frac{3(5N+4)}{\pi^2 N(5N+2)}
\end{aligned}
\tag{4.12}
$$

The Fisher-type tests assume cross sectional independency, which requires that the individual cross-sections in the dataset do not correlate with each other (Choi, 2001). Based on the data used, this assumption may be unrealistic and, therefore, violated. For this reason, we additionally apply Pesaran's unit root test to avoid spurious inferences due to possibly skewed test results. The test employs a cross-sectional augmented Dickey-Fuller (ADF) approach, which involves augmenting the regressions with the cross-sectional averages of lagged levels and first-differences of the individual series (Pesaran, 2007).

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5 Is there a Green Discount in Commercial Real Estate Lending?

5.1 Abstract

Purpose: This study examines whether green buildings enjoy more favorable financing terms compared to their non-green counterparts, exploring the presence of a green discount in commercial real estate lending. Despite the extensive research on green premiums on the equity side, lending has received limited attention in the existing literature, even as regulations have increased and ambitious net-zero targets have been set in the banking sector.
Design/methodology/approach: In this study, we leverage a unique dataset comprising European commercial loan data spanning from 2018 to 2023, with a total loan value exceeding €30 billion. We employ hedonic regression models to analyze the data. Specifically, we rely on property assessments conducted by lenders to investigate whether green properties exhibit lower interest rate spreads and higher LTV ratios.
Findings: Our findings reveal the existence of a green discount in European commercial real estate lending, with green buildings enjoying a 5.35% lower contracted loan spread and a 3.92% lower target spread compared to their non-green counterparts. However, our analysis does not indicate any distinct advantage in terms of LTV ratios for green buildings.
Originality/value: This study, to the best of our knowledge, represents the first of its kind in a European context and provides empirical evidence for the presence of a green discount.
Practical implications: Our research contributes to a deeper understanding of the interaction between green properties and commercial real estate lending, offering valuable insights for both lenders and investors.

Keywords: *Commercial Real Estate Lending; Sustainable Finance, Green Discount.*

5.2 Introduction and Background Literature

Building on the UN Sustainable Development Goals (SDGs) and the Paris Agreement, sustainable finance and investment have emerged as a transformative approach that aims to integrate ESG considerations into financial decision-making processes. This paradigm shift has taken hold in various industries, and the property sector is no exception. Most market participants have become aware of the real estate industry's major responsibility in the transition to a carbon-neutral economy and to the importance of realigning capital flows accordingly. In this context, it is evident that sustainable property investments are not solely driven by philanthropic motives. Extensive research conducted over the last decade has revealed that sustainable properties are linked to a green premium on the equity side. In literature, green and non-green properties are predominantly differentiated based on either common certification schemes such as LEED, BREEAM, and ENERGY STAR or national energy performance certificates. The primary focus of studies within the commercial real estate sector revolves around office buildings, revealing a connection between property certification and higher rents, prices, as well as enhanced operational performance (Wiley et al., 2010; Eichholtz et al., 2010; Fuerst & McAllister, 2011a; Reichardt et al., 2012; Eichholtz et al., 2013; Chegut et al., 2014; Holtermans & Kok, 2019). Similar green premiums have been observed in real estate markets across the United States, Asia, and Europe for both single- and multi-family residential properties (Deng et al., 2012; Kahn & Kok, 2014; Fuerst et al., 2015; Bond & Devine, 2016; Cajias et al., 2019; Cadena & Thomson, 2021; Dell'Anna & Bottero, 2021). In addition to studies that focus on the property level, another body of literature highlights the positive impact of holding green properties on the corporate level of REITs (Eichholtz et al., 2012; Sah et al., 2013; Fuerst, 2015; Ooi & Dung, 2019; Devine & Yönder, 2021). Despite the evident long-term demand-side benefits leading to a green premium for property owners, the adoption of new green construction and retrofitting has not surged as one would expect. Chegut et al. (2019) attribute this inefficiency in the market to the lack of short-term incentives for the supply side and further point out that longer construction times and higher upfront costs for green construction are an obstacle for equity-constrained developers. Lenders in particular have the capability to remove potential barriers to entry for real estate developers by offering lower rates and LTV ratios, effectively addressing potential short-term capital shortages (Chegut et al., 2019; Mathew et al., 2021).

The necessity of debt capital in financing a carbon-neutral economy is becoming increasingly apparent to banks. For example, ambitions at the global level are reflected in the United Nations Net Zero Banking Alliance (NZBA), which assembles 126 banks from 41 different countries with a total of over 40% of global banking assets (UNEP FI, 2021b). To this end, NZBA has released the Guidelines for Climate Change Target Setting (UNEP FI, 2021a). Furthermore, the UN Principles for Responsible Banking serve as a voluntary framework for banks to align their strategies with the UN Sustainable Development Goals (UNEP FI, 2019). Other initiatives with global reach, such as Partnership for Carbon Accounting Financials (PCAF), Network for Greening the Financial System (NGFS), and Task Force on Climate-related Financial Disclosures (TCFD), complement legally binding (EU-)frameworks such as the EU taxonomy or the Corporate Sustainability Reporting Directive (CSRD). As a component of the EU taxonomy, a novel financial metric emerges: the GAR, slated for mandatory reporting by banks starting in 2024. Although there are currently no legally binding benchmarks for achieving a specific GAR, financial institutions could increase their efforts to promote green lending and actively participate in the discernible shift toward quantifying green assets in their portfolios. The rising global requirements for (sustainability) reporting can continue to result in banks raising their assessment criteria for the properties eligible for financing. In the event that banks are committed to Net-Zero goals—whether voluntarily or through regulatory requirements—the portfolio of properties financed may be influenced by this commitment. Consequently, an increase in the GAR as well as potential incentivization is anticipated for numerous lenders.

Although some residential lenders already provide incentives for green properties, such as additional loan proceeds and lower spreads, a green discount is not yet openly promoted in commercial real estate lending (Mathew et al., 2021). Despite usually not being explicitly advertised during loan origination, the question arises as to whether a green discount for commercial property loans is still observable, particularly when considering green real estate from a risk perspective and the imperative for lenders to enhance the proportion of green real estate in their new business. To this date, only a limited number of studies in the realm of sustainable real estate focus on the debt side of properties. Devine and McCollum (2021) analyzed mortgage-backed securities data from Fannie Mae and discovered that loans for green multifamily properties, backed by green bonds, exhibit lower interest rates and lower debt service coverage ratios. Their findings reveal that loan packages committed to reducing carbon emissions are linked to higher loan-to-value ratios and greater debt levels per building unit, even after accounting for loan and property characteristics. Eichholtz et al. (2019) found that commercial mortgages on buildings owned by REITs and certified with LEED or ENERGY STAR experience notably lower spreads. Attributed to reduced bond spreads, REITs holding a higher proportion of certified buildings also benefit from more advantageous corporate-level financing in the secondary market. For REITs investing in office and retail properties, Devine and Yönder (2021) also observed that, regardless of the differences in quality characteristics, lenders attribute lower risk to pure participation in green certification schemes, which leads to lower interest costs at the corporate level. Based on CMBS loan data secured by individual properties from 2000 to 2013, research by An and Pivo (2020) revealed that LEED and ENERGY STAR certified buildings exhibit notably lower default risk. This reduction can be attributed not only to the certification itself but also to the actual level of green achievement. Although the decrease in default risk economically outweighs the impact on spreads at loan origination, their study indeed highlights lower spreads for green properties during the origination process. Upon examination of sub-periods, they observed that the green discount in spreads began to emerge gradually from 2006 onwards, and became even more pronounced following the financial crisis.

We aim to extend existing research by analyzing the influence of a property's categorization as either green or non-green on spreads and LTV ratios in commercial real estate lending. This allows us to determine the potential of lenders to both mitigate entry barriers for the supply side of green properties and to enhance the own portfolio's green asset ratio. Within our analysis, a distinction is established between the target spread, denoting the minimum spread derived from lender's internal pre-calculations, and the spread that is contractually agreed. A differentiated view further enables us to identify a potential pricing effect on green properties between internal calculation and the spreads effectively conveyed during the loan origination process. Given that prior studies predominantly rely on data of listed real estate, focus on owner-occupied residential lending exclusively, or examine periods when lenders were only beginning to distinguish between green and non-green properties, the empirical evidence for benefits on the debt side of green properties is very limited. To the best of our knowledge, our study is the first to examine the green discount at the loan-level within a European context, using the most recent data available. Moreover, our focus diverges from external commercial certification schemes, which are based on voluntary participation, to the actual energy intensity of buildings. This aspect is increasingly garnering attention from lenders due to mounting regulatory pressures. Our empirical analysis is based on a unique dataset consisting of 728 commercial real estate loans across a range of property types, spanning from 2018 through 2023. In the following part of this paper, besides providing a more comprehensive outline of the dataset and descriptive statistics, we will describe the loan criteria applied to categorize properties as either green or non-green. Subsequently, we will delineate our methodological approach and present the results along with their implications. The paper ends with our final conclusions.

5.3 Data and Descriptive Statistics

The cross-sectional dataset underlying our analysis was provided by one of Germany's largest commercial real estate lenders. It encompasses European new commercial transactions consisting of 728 loans, amounting to a total volume of over €30 billion, spanning from January 2018 to June 2023. The frequency of loan approvals remains constant over time, with the highest number of transactions occurring in 2019, accounting for 21% of all observations in our sample. The loan data is solely related to investment properties. Furthermore, in the context of residential real estate, we specifically focused on acquiring loans designated for investment purposes. This focus is essential, as it significantly influences risk assessment and the corresponding terms of the loan, depending on whether the property is owner-occupied or intended for income generation. We employ the loan spreads and LTV ratios in our sample to identify the presence of a potential green discount.

In financial market theory, the nominal interest rate is composed of both time and risk components for which a lender must be compensated in order to lend money. Fisher (1930) describes the nominal interest rate as the sum of real interest rate and expected inflation. In addition to the real rate and expected inflation, the liquidity premium which incorporates the loan maturity is considered as a further time component. The risk component of the nominal rate consists of the specific risks and the systematic risks. Typically, specific risks are related to loan and property characteristics, such as customer-specific risk classification (including investor profile), LTV, loan volume, location, and property type. The relevant descriptive statistics can be found in Table 5.1. In our analysis, it is crucial to note that the actual component of time risk is explicitly and independently quantified as a separate funding spread by the lender. To mitigate heterogeneity concerns across different loans in relation to time risks and fluctuations in the real rate, we explicitly requested an adjustment for both the funding spread and the base rate. Therefore, these spreads have been adjusted for all maturity-based risk factors, such as the loan maturity, the type of loan (whether amortization or bullet loan), and the nature of the base rate (fixed or variable). The spreads observed in our dataset predominantly reflect the specific and systematic risk components, internal costs, and loan origination fees.

Table 5.1: Summary Statistics of the Sample

Variable	N	Mean	Std. dev.	Min	Q25	Q75	Max
Spread	728	1.30	0.55	0.39	0.94	1.70	4.30
Target spread	728	1.30	0.49	0	0.93	1.60	4.40
LTV (in %)	728	61	17	11	50	70	163
Volume (in t. €)	728	40,770	46,775	0.01	11,000	54,000	550,000
Maturity (in months)	728	73	45	3	36	120	360
Green building	728	33%					
Investor profile	728						
Developer	150	21%					
Fund	35	5%					
Foreign investor	213	29%					
Domestic investor	202	28%					
Investment management	76	10%					
Housing company	52	7%					
Customer rating	728						
Customer rating 1	212	29%					
Customer rating 2	178	24%					
Customer rating 3	229	31%					
Customer rating 4	100	14%					
Customer rating 5	9	1%					
Property type	728						
Office	305	42%					
Retail	85	12%					
Specialty retail center	10	1%					
Hotel	5	1%					
Department store	5	1%					
Logistics	80	11%					
Management property	15	2%					
Parking garage	4	1%					
Mall	3	0%					
Residential investment	205	28%					
Social property	2	0%					
Other	9	1%					
Region	728						
DE: old states A-cities	185	25%					
DE: old states B-cities	90	12%					
DE: old States (other)	108	15%					
DE: new States A-cities	25	3%					
DE: new States (other)	23	3%					
DE: Berlin	115	16%					

Continued on next page

Table 5.1: Summary Statistics of the Sample (Continued)

Belgium	4	1%
France	38	5%
Great Britain	1	0%
Luxembourg	1	0%
Netherlands	99	14%
Poland	38	5%
Other countries	1	0%
Year	728	
2018	124	17%
2019	156	21%
2020	142	20%
2021	135	19%
2022	138	19%
2023	33	5%

As is evident from Figure 5.1, the spread data does not follow a normal distribution. This observation is confirmed by the results of the Jarque and Bera (1980) test, with the null hypothesis of normally distributed data (p-value = 0, Kurtosis: 5.53, Skewness: 1.11). By applying a logarithmic transformation to the data, as depicted in Figure 5.2, we attain a normal distribution, which is a fundamental assumption of the models employed in our analysis. This observation is supported by the Jarque-Bera test (p-value > 0.18, Kurtosis: 2.82, Skewness: -0.14). Similar observations are made for the target spread data.

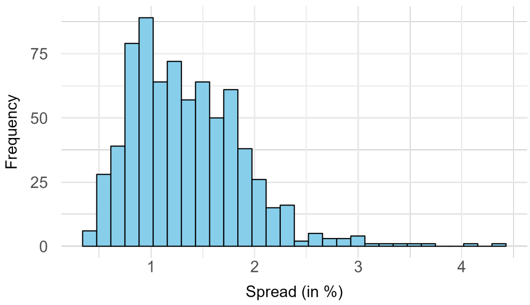

Figure 5.1: Spread Histogram

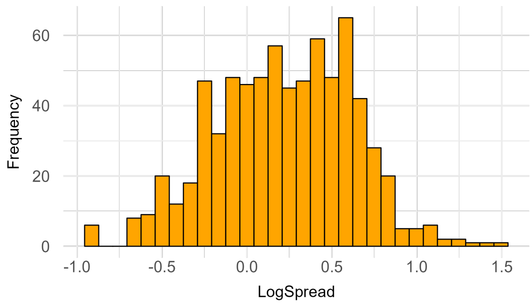

Figure 5.2: LogSpread Histogram

The lender's customer rating system comprises risk classes numbered from 1 (representing the lowest risk) to 5 (indicating the highest risk). Within this framework, a notable segment (31%) of customers is categorized as class 3, while the second-largest class is class 1, comprising 29%. Class 5 (representing the highest level of risk) constitutes less than 2% of the loans. Figure 5.3 illustrates that a greater risk appears to necessitate a higher spread. Figure 5.4 displays the allocation of loan frequency based on the respective investor profiles. It indicates that a significant portion of loans was extended to both foreign and domestic investors, comprising 57% of the total. Notably, a slightly greater proportion of these loans was allocated to foreign investors. The smallest portion pertains to funds (5%). On average, the bank establishes a target spread of 1.30 percentage points above the given interest rate for these transactions. Correspondingly, the actual spread realized in the loan contracts aligns with this target, averaging at the same level. In our sample, properties are financed at an LTV of 61%, accompanied by an estimated standard deviation of 16.57. The average loan size is just over €40 million, which could correspond to a single asset or multiple similar properties financed together. The average term to maturity in our sample is 6 years. While foreign investors contribute a significant absolute volume of loans, approximately three quarters of the total funded amount remains within Germany. The Netherlands rank second (13%), followed by France (7%) and Poland (5%). Office and residential properties make up a clear focus in the portfolio, accounting for a total of 70% of loans. The other property types, except for retail (12%) and logistics (11%), are only sporadically represented in our sample.

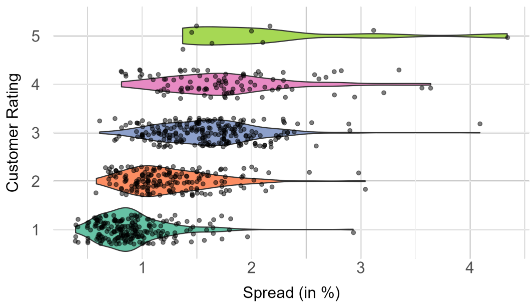

Figure 5.3: Violin Plot of Customer Ratings vs. Spread in %

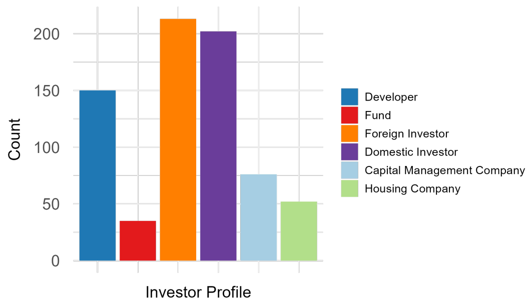

Figure 5.4: Bar Plot of Loan Counts by Investor Profiles

In the analysis of green properties, existing energy performance certificates are frequently used as a benchmark for ecological performance (Cajias et al., 2019; Fuerst et al., 2015; Fuerst & McAllister, 2011b). Energy certificates allow for a standardized and clear-cut benchmarking process. However, in light of the prevailing regulatory demands and the intensifying pressures of the market, this relatively straightforward classification is progressively proving insufficient. Within the European context relevant to our dataset, the EU taxonomy regulation stipulates that existing buildings can be classified as sustainable if they belong to the top 15% in terms of energy efficiency

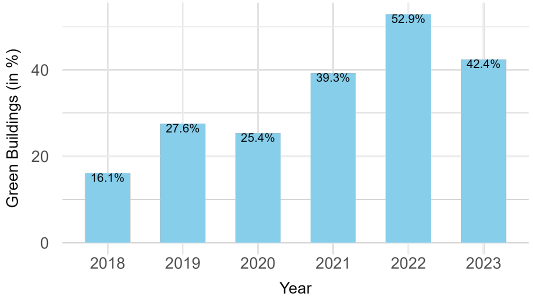

Figure 5.5: Green Asset Ratio in % of Loans per Year

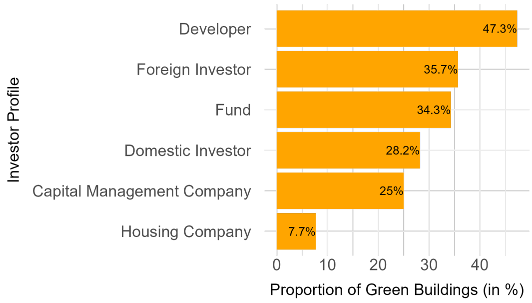

Figure 5.6: Green Asset Ratio in % of Total Loans per Investor Profile

within the national or regional building stock. Therefore, to derive a binary variable that categorizes properties as non-green or green, a comprehensive examination of current regulatory guidelines, available data, and relevant key performance indicators is necessary. In the sample of buildings we analyzed, the green building variable classifies properties as green if they either (1) exhibit exceptional energy efficiency or (2) adhere to the technical criteria set forth in the EU taxonomy regulation for buildings. The first set of criteria was introduced by the financial institution prior to the publication of the EU taxonomy criteria and was subsequently complemented by the second set to align with the EU taxonomy requirements. Generally, a building qualifies as a green building if it meets at least energy performance certificate class A, does not exceed specific energy demand thresholds per square meter, holds a high level of sustainability certifications, and/ or complies with the EU taxonomy criteria for existing buildings, new construction, or renovations. Hence, the principal criterion for a green loan in our dataset is the aggregate best-in-class energy requirement for heating and electricity, aimed at precluding buildings with a suboptimal energy performance in terms of building envelope or those with a disproportionately high energy demand from qualifying for a green loan. Moreover, older buildings are eligible for a green loan either by aligning with the best-in-class of the top 15 percent of the national or regional building standards, or through energy modernization and a reduction of primary energy demand by 30%. The focus on energy intensities is in line with the 'efficiency first principle' as outlined in the European Parliament (2023). This approach is pivotal, as energy savings are not only a feasible method for reducing carbon emissions but also, even under the most optimistic scenarios, there is an anticipated limitation in the availability of renewable energy for building operations by 2050, as projected by the IEA (International Energy Agency, 2021).

Within our dataset, the proportion of green buildings is approximately 33%, with the share showing a tendency to increase over time (see Figure 5.5). As shown in Figure 5.6, developers constitute the largest share at 47%, while housing companies represent the smallest share at 8% in terms of green buildings within our sample. This observation may be attributed to the distinction between new construction and existing stock. Developers typically engage in new construction or extensive revitalization, whereas housing companies often acquire substantial portions of their portfolios from existing stock. With regard to real estate values, which can be estimated by extrapolating average LTVs and loan volumes, our findings align with those of Eichholtz et al. (2019) in that green properties, on average, command a higher value of approximately €75 million compared to non-green properties at €63 million.

5.4 Empirical Framework

In order to identify and isolate the potential impact of property categorization as green or non-green on loan spreads and LTV, while also accounting for other explanatory loan characteristics, we employ a hedonic regression model based on the framework first introduced by Rosen (1974). According to Fuerst and McAllister (2011a) this methodology is used as the primary framework for analyzing the factors that determine pricing effects in real estate research and is therefore commonly applied in empirical studies examining the green premium in property markets (Eichholtz et al., 2010; Fuerst & McAllister, 2011a; Bond & Devine, 2016; Holtermans & Kok, 2019). Within the ambit of this methodology, individual characteristics of each loan, encompassing elements like property type, region, or year, are assigned specific hedonic weights. These weights represent the distinct value contributions of each characteristic to the overall loan spread. Employing this empirical framework facilitates a targeted isolation and precise quantification of the value contribution ascribed to the classification of a property as a green property.

$$\log S_i = \alpha + \beta_i X_i + \delta g_i + \sum_{j=1}^{J} \gamma_j c_{ij} + \sum_{t=1}^{T} \lambda_t h_{it} + \epsilon_i \tag{5.1}$$

$$\log S_i = \alpha + \beta_i X_i + \delta g_i + \sum_{j=1}^{J} \gamma_j c_{ij} + \sum_{t=1}^{T} \lambda_t h_{it} + \sum_{t=1}^{T} \theta_t h_{it} g_i + \epsilon_i \tag{5.2}$$

We define the functional form of the hedonic regression function as semi-log with the (target) spread as the logarithmized dependent variable S_i. According to Sirmans et al. (2005), the semi-log model offers two decisive advantages over the linear form. On one hand, the value of a specific characteristic can vary proportionally with that of another characteristic. On the other hand, logarithmization can help mitigate heteroscedasticity, thus reducing changes in the variance of the residuals. Moreover, if the dependent variable is skewed, applying logarithmization can help to obtain a distribution which follows a normal distribution more closely (see Figure 5.1 and 5.2). X_i denotes a vector of the hedonic loan characteristics described in the initial section of the paper, including factors such as property type, initial loan size, or maturity. g_i defines the dummy variable that is crucial for our research question. It takes a value of 1 if the lender categorizes the property as green, and zero otherwise. As highlighted by An and Pivo (2020), addressing endogeneity bias, which often stems from the unobserved heterogeneity among different properties, is crucial in research focused on accurately isolating the green premium. Ignoring vital influencing factors in the model can lead to spurious regression results, thereby distorting interpretations and compromising the validity of conclusions. To counteract this issue effectively, our models integrate both location-specific (c_{ij}) and time-specific (h_{it}) fixed effects. This approach ensures a nuanced capture of the distinct characteristics and temporal dynamics inherent to each cluster, thus fostering a more accurate and reliable analytical outcome. β_i, δ, γ_j, and λ_t are estimated coefficients of the explanatory variables. ϵ_i is an error term. The inclusion of an additional interaction term between the two dummy variables h_{it} and g_i in Equation 2 allows us to detect a potential change in the impact of property categorization on spreads over time, reflecting the pattern of green discount found by An and Pivo (2020).

$$L_i = \alpha + \beta_i X_i + \delta g_i + \sum_{j=1}^{J} \gamma_j c_{ij} + \sum_{t=1}^{T} \lambda_t h_{it} + \sum_{t=1}^{T} \theta_t h_{it} g_i + \epsilon_i \tag{5.3}$$

The same methodological framework is applied in Equation 3 to determine a potential influence of the building categorization on LTVs, resulting in additional loan proceeds for green properties. As we did not identify any benefits from applying a logarithmic transformation to the dependent variable L_i, we opted for a linear form for these models. Although the semi-log model contributes to mitigating heteroscedasticity, the Breusch and Pagan (1979) test is applied to detect significant changes in the variance of the residuals across all models. Persisting heteroscedasticity is corrected for by using a heteroskedasticity-consistent covariance matrix estimator (White, 1980). Another issue in hedonic regression analysis that may cause the regression results to be biased is multicollinearity, a situation where two or more independent variables are highly correlated. Beyond examining the correlations among individual predictors, the variance inflation factor (VIF) and the generalized variance inflation factor (GVIF) for categorical variables enable us to identify which specific variables are affected by multicollinearity. When comparing GVIFs, Fox and Monette (1992) recommend using the modification GVIF$^{(1/(2*Df))}$ with Df degress of freedom, as this ensures comparability across dimension. A value of 10 or higher is considered a common rule of thumb for a high degree of multicollinearity, suggesting a need to correct the independent variable accordingly. As outlined by O'brien (2007), we consider additional factors such as t-values and confidence intervals that affect the stability of the estimates, so that reliable statistical inferences might be drawn even with elevated VIF or GVIF values. Our analysis encompasses a total of twelve models. There are four models each for target spread, spread, and LTV as dependent variables. In each case, Model 1 provides the baseline model, while Models 2 and 3 introduce time and regional effects. Model 4 expands Model 3 by including an interaction term between the green building dummy and the time dummy.

5.5 Empirical Results and Implications

Our analysis comprises a total of 12 hedonic models evenly distributed across the three predefined dependent variables ($LogSpread$, $LogTargetSpread$, and LTV). As described, the respective Model 1 serves as the base model, which is augmented with regional and time effects in Models 2 and 3, respectively. In terms of our research question, the independent green building dummy is central to our analysis. In this context, a value of 0 denotes non-green buildings, while a value of 1 signifies green buildings. Model 4 further incorporates an interaction term between the year and green building variables to account for potential time effects with regard to green building. In addition to continuous variables such as loan volume, term to maturity, and (target) spread or LTV, we address the heterogeneity in loan data by incorporating investor profile, customer rating (ranging from 1 for low risk to 5 for high risk), and property type.

The metrics adjusted R^2, AIC, BIC, and RMSE facilitate the identification of the models that have the best goodness of fit for each corresponding dependent variable. In Table 5.2, regarding the dependent variable $LogSpread$, Model 3 emerges as the preferred choice. Consequently, coefficients are interpreted with reference to Model 3. Notably, the adjusted R^2 is close to 0.7, and we observe the lowest values for AIC and BIC. In addition, there is consistency in the RMSE, which is 0.22 for both Model 3 and Model 4. An examination of the confidence intervals as well as the VIF and GVIF values shown in Table 5.5 in the Appendix does not reveal any unexpected multicollinearity. We observe analogous results in the models with $LogTargetSpread$ and LTV as the dependent variables.

Table 5.2: Hedonic Model Results where $y = LogSpread$

Model	1	2	3	4
(Intercept)	0.210*** (0.059)	0.206*** (0.059)	0.091 (0.061)	0.086 (0.062)
Green building	0.006 (0.021)	-0.010 (0.021)	-0.055** (0.020)	-0.032 (0.058)
LTV (in %)	0.002*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Volume (in t. €)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Maturity (in months)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Investor profile (ref: developer)				
Fund	-0.197*** (0.053)	-0.223*** (0.053)	-0.242*** (0.050)	-0.243*** (0.051)
Foreign investor	-0.131*** (0.031)	-0.252*** (0.037)	-0.276*** (0.035)	-0.274*** (0.035)
Domestic investor	-0.140*** (0.031)	-0.151*** (0.030)	-0.164*** (0.029)	-0.163*** (0.029)
Investment management	-0.360*** (0.043)	-0.380*** (0.043)	-0.384*** (0.041)	-0.380*** (0.041)
Housing company	-0.389*** (0.050)	-0.438*** (0.051)	-0.469*** (0.049)	-0.467*** (0.049)
Customer rating (ref: 1)				
Customer rating 2	0.163*** (0.028)	0.156*** (0.027)	0.171*** (0.026)	0.172*** (0.026)
Customer rating 3	0.334*** (0.028)	0.307*** (0.028)	0.302*** (0.027)	0.300*** (0.027)
Customer rating 4	0.397*** (0.034)	0.368*** (0.034)	0.358*** (0.033)	0.358*** (0.033)
Customer rating 5	0.526*** (0.086)	0.528*** (0.085)	0.476*** (0.081)	0.471*** (0.081)
Property type (ref: office)				
Retail	-0.064+ (0.033)	-0.058+ (0.034)	-0.053+ (0.032)	-0.051 (0.032)
Specialty retail center	0.126 (0.079)	0.096 (0.079)	0.002 (0.076)	-0.003 (0.077)
Hotel	0.271* (0.111)	0.270* (0.108)	0.218* (0.104)	0.222* (0.104)
Department store	0.146 (0.111)	0.198+ (0.110)	0.114 (0.106)	0.106 (0.106)
Logistics	-0.042 (0.031)	-0.032 (0.033)	-0.044 (0.031)	-0.043 (0.032)
Management property	-0.057 (0.065)	-0.046 (0.064)	-0.012 (0.061)	-0.006 (0.061)
Parking garage	0.408** (0.125)	0.278* (0.125)	0.144 (0.121)	0.136 (0.122)
Mall	0.262+ (0.143)	0.252+ (0.140)	0.186 (0.134)	0.184 (0.135)
Residential investment	-0.131*** (0.025)	-0.127*** (0.024)	-0.153*** (0.024)	-0.154*** (0.024)
Social property	0.187 (0.176)	0.204 (0.171)	0.176 (0.164)	0.187 (0.164)
Other	0.010 (0.083)	0.022 (0.081)	0.029 (0.078)	0.024 (0.078)
Region (ref: DE: old states A-cities)				
DE: old states B-cities		0.001 (0.033)	-0.005 (0.031)	-0.005 (0.032)
DE: old states (other)		0.005 (0.032)	0.020 (0.031)	0.017 (0.031)
DE: new states B-cities		0.114* (0.053)	0.120* (0.050)	0.120* (0.050)
DE: new states (other)		0.043 (0.056)	0.024 (0.054)	0.021 (0.054)
DE: Berlin		0.021 (0.029)	0.027 (0.028)	0.027 (0.028)
Belgium		-0.052 (0.122)	-0.020 (0.117)	-0.027 (0.119)
France		0.021 (0.050)	0.041 (0.048)	0.043 (0.048)
Great Britain		0.147 (0.240)	0.056 (0.229)	0.044 (0.230)
Luxembourg		0.111 (0.240)	0.215 (0.229)	0.218 (0.232)
Netherlands		0.181*** (0.039)	0.194*** (0.037)	0.189*** (0.037)

Continued on next page

Table 5.2: Hedonic Model Results where $y = LogSpread$ (Continued)

Poland		0.303*** (0.051)	0.312*** (0.049)	0.311*** (0.049)
Other countries		-0.051 (0.240)	-0.086 (0.229)	-0.098 (0.230)
Year (ref: 2018)				
Year 2019			0.023 (0.028)	0.027 (0.032)
Year 2020			0.093** (0.029)	0.083* (0.033)
Year 2021			0.131*** (0.030)	0.146*** (0.036)
Year 2022			0.203*** (0.030)	0.217*** (0.038)
Year 2023			0.273*** (0.046)	0.292*** (0.059)
Green building x 2019				-0.025 (0.070)
Green building x 2020				0.031 (0.072)
Green building x 2021				-0.049 (0.070)
Green building x 2022				-0.040 (0.069)
Green building x 2023				-0.056 (0.100)
Num.obs.	728	728	728	728
R^2	0.650	0.676	0.708	0.709
R^2 adj.	0.638	0.659	0.691	0.690
AIC	35.6	3.6	-63.4	-55.9
BIC	155.0	178.1	134.0	164.4
RMSE	0.24	0.23	0.22	0.22
Regional effects	N	Y	Y	Y
Time effects	N	N	Y	Y

Note: The standard errors are indicated in parentheses. The levels of statistical significance are represented as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Model 3 and 4 are estimated using heteroskedasticity-robust covariance matrix estimators. The variable green building is a dummy variable that is one if the respective asset is classified as a green building by the lender, according to the classification described in the text. The categorical variables for investor profile describe the classification of the type of investor made by the lender and is independent of the financed asset. The variable customer rating describes the risk classification of the customer made by the lender, where 1 = least risky and 5 = most risky, and is also independent of the asset. The year refers to the year of financing issuance. The interaction term between year and green building is one if a financed asset was classified as green in the respective years.

The combined influence of these variables provides insights into how different loan and borrower characteristics affect the lender's spread requirements. It becomes apparent that loan-related factors, specifically LTV, loan volume (which appears to have no significant impact), and term to maturity, exert only minimal influence on the spread. The limited impact of maturity on spreads aligns with our expectations. As outlined in the descriptive statistics, this can be attributed to the fact that maturity-related effects are predominantly accounted for by the lender's distinct funding spread, resulting in only a marginal effect on the dependent (target) spread variables. The categorical variable investor profile, in conjunction with customer rating, represents the customer profile. With developer serving as the reference category, negative coefficients of the remaining variables indicate that developers pay the highest spreads. In addition to the inherently higher risk for developers compared to investors pursuing buy and hold strategies, the recourse options for lenders in these cases are often limited due to special purpose entities established for developments. For joint ventures or general and limited partner situations, underwriting for lenders, especially with recourse options, is not straightforward and often entails higher complexity. That is because other assets that are used as collateral need also to be assessed thoroughly. Although there are notable differences in underwriting requirements and pricing between an investment loan and a development loan, we can effectively control for these variations. Firstly, the maturity-specific risks, as previously mentioned, are not included in the spreads under examination. Secondly, as shown in Tables 5.2 through 5.4, the highly significant hedonic weights of all investor types indicate that our statistical models are capable of isolating the influences of various loan types. The lowest spread is paid by housing companies (-0.469 or -37.44%). Coefficients in Model 3 for customer rating align with intuitive expectations - higher risk categories correspond to higher spread levels. The values of the coefficients increase from the reference category Customer Rating 1 to the highest risk category Customer Rating 5, amounting to 0.476, equivalent to an increase in spreads of nearly 71%.

Property type and location-specific parameters (regional effects), along with the green building variable, collectively account for the building-specific characteristics within our sample. Unlike the investor profile variables, only a small subset of the building-specific characteristics significantly affects $LogSpread$. Among property types (with office as the reference category), three out of eleven coefficients lie within the defined significance level of 0.1. Retail properties experience a decrease of -0.053 or -5.16%, whereas hotels demonstrate an increase of 0.218 or 24.38% compared to offices. Similar to the reduction observed for housing companies, there is a decrease evident for residential properties, which might be attributed to the availability of promotional loans for residential buildings. As indicated by a strongly significant coefficient of -0.153, the lender realizes 14.19% less spread. The location-specific parameters encompass 13 locations (country, German federal state, or city level), with Germany: old states A-cities serving as the reference category. However, only three of these parameters exhibit a significant influence on the dependent variable. The most pronounced increase in spreads is observed for Poland, amounting to 0.312 or 36.62% compared to Germany: old states A-cities. This observation is consistent with Poland's higher property yield environment compared to other European countries covered in our analysis. The aforementioned adjustments for customer and building characteristics mirror the bank's individual assessment of risk-return profiles.

The time effects, using the reference year 2018 to account for year-specific characteristics, are statistically significant for all years except for 2019. It can be observed that the annual effects on the *LogSpread* steadily increase over time. The explanatory power can be further enhanced by considering the time dimension when comparing the goodness of fit between Model 2 and Model 3, two models that differ only in the inclusion of time effects. The introduction of the interaction term between the year and the green building variable in Model 4 does not improve the model's performance any further and also lacks statistical significance. Hence, contrary to the findings of An and Pivo (2020), we cannot observe a change in the impact of green building classification on credit spreads over the years. Moreover, the inclusion of the interaction term leads to an approximate tripling of the modified GVIF factor for the green building variable, indicating a substantial increase in multicollinearity.

In Model 3, the green building variable exhibits a highly significant coefficient of -0.055, resulting in a reduction in spreads of approximately 5.35%. Given the average loan size in our sample of €40.77 million and an average spread of 130 bps, this translates into a green discount of approximately 7 bps. This green discount corresponds to an interest saving of approximately €28,356 for borrowers in the first year. In contrast to the coefficients of other independent variables in the model, the green discount may seem relatively modest. However, in the context of our research question, the finding of a green discount in European commercial lending is novel. The reduction in spreads we observe is somewhat less pronounced when compared to the findings of Eichholtz et al. (2019). Their research shows a green discount ranging from 24 to 29 bps, depending on the specifications of the green-certified property, with a relative spread reduction of 7.95 to 9.60%. In contrast to our dataset and the methodology employed by An and Pivo (2020), Eichholtz et al. (2019) derive the spread by utilizing mortgage rates sourced from U.S. REIT data and subtracting the corresponding treasury rate based on mortgage rate maturity. Our results are more in line with those of An and Pivo (2020), indicating a green discount of 5.85%. Based on the limited empirical evidence available, the findings cautiously support the conclusion that a comparable green discount exists in both the European and U.S. commercial real estate markets.

Table 5.3 presents the results of the models with the *LogTargetSpread* as the dependent variable. These findings largely align with the results of the models outlined above. Model 3 once again exhibits the highest goodness of fit. Notable deviations are observed in certain coefficients. For example, in the case of customer ratings, which reflect the same reference variable, the coefficients now have a higher average value. Specifically, the riskiest customer rating category 5 is now associated with a significantly higher coefficient of 0.841 or 131.87% compared to the reference category of customer rating

1. Regarding property types, it is noteworthy that the coefficient for the mall variable becomes negative, implying a lower target spread as for offices, all else being equal. This finding is rather surprising in light of the increasing pressures from e-commerce and the post-COVID environment. In terms of cities, the coefficient for Luxembourg turns statistically significant and positive (0.533 or 70.40% compared to the reference Germany: old states A-cities).

Table 5.3: Hedonic Model Results where $y = LogTargetSpread$

Model	1	2	3	4
(Intercept)	-0.020 (0.059)	-0.012 (0.060)	-0.206*** (0.059)	-0.220*** (0.060)
Green building	0.038+ (0.021)	0.019 (0.021)	-0.040* (0.020)	0.017 (0.056)
LTV (in %)	0.001* (0.001)	0.002* (0.001)	0.002*** (0.001)	0.002*** (0.001)
Volume (in t. €)	0.000 (0.000)	0.000 (0.000)	0.000+ (0.000)	0.000 (0.000)
Maturity (in months)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000+ (0.000)
Investor profile (ref: developer)				
Fund	-0.150** (0.053)	-0.191*** (0.053)	-0.230*** (0.049)	-0.231*** (0.049)
Foreign investor	-0.136*** (0.031)	-0.262*** (0.037)	-0.286*** (0.034)	-0.286*** (0.034)
Domestic investor	-0.149*** (0.031)	-0.158*** (0.031)	-0.171*** (0.028)	-0.170*** (0.028)
Investment management	-0.204*** (0.043)	-0.236*** (0.044)	-0.249*** (0.040)	-0.247*** (0.040)
Housing company	-0.297*** (0.050)	-0.348*** (0.051)	-0.377*** (0.047)	-0.369*** (0.048)
Customer rating (ref: 1)				
Customer rating 2	0.141*** (0.028)	0.124*** (0.027)	0.146*** (0.025)	0.146*** (0.025)
Customer rating 3	0.445*** (0.028)	0.421*** (0.028)	0.411*** (0.026)	0.411*** (0.026)
Customer rating 4	0.555*** (0.034)	0.526*** (0.035)	0.510*** (0.032)	0.509*** (0.032)
Customer rating 5	0.962*** (0.087)	0.921*** (0.086)	0.841*** (0.078)	0.831*** (0.079)
Property type (ref: office)				
Retail	-0.026 (0.033)	-0.003 (0.034)	-0.001 (0.031)	-0.001 (0.031)
Specialty retail centers	0.150+ (0.080)	0.153+ (0.080)	0.030 (0.074)	0.034 (0.074)
Hotel	0.321** (0.112)	0.337** (0.110)	0.246* (0.100)	0.256* (0.101)
Department store	0.170 (0.111)	0.124 (0.111)	-0.015 (0.102)	-0.030 (0.103)
Logistics	0.033 (0.031)	0.049 (0.033)	0.027 (0.030)	0.023 (0.030)
Management properties	-0.107 (0.065)	-0.093 (0.065)	-0.049 (0.059)	-0.046 (0.059)
Parking garage	0.497*** (0.125)	0.414** (0.127)	0.245* (0.117)	0.240* (0.118)
Mall	-0.348* (0.143)	-0.385** (0.142)	-0.489*** (0.129)	-0.483*** (0.130)
Residential investment	-0.124*** (0.025)	-0.106*** (0.025)	-0.142*** (0.023)	-0.144*** (0.023)
Social property	0.498** (0.176)	0.496** (0.173)	0.445** (0.158)	0.448** (0.158)
Other	-0.338*** (0.084)	-0.313*** (0.082)	-0.316*** (0.075)	-0.321*** (0.076)
Region (ref: DE: old states A-cities)				
DE: old states B-cities		0.053 (0.033)	0.054+ (0.030)	0.059+ (0.031)

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Table 5.3: Hedonic Model Results where $y = LogTargetSpread$ (Continued)

DE: old states (other)		-0.037 (0.033)	0.007 (0.030)	0.011 (0.030)
DE: new states B-cities		0.023 (0.053)	0.037 (0.049)	0.041 (0.049)
DE: new states (other)		-0.038 (0.057)	-0.045 (0.052)	-0.039 (0.052)
DE: Berlin		0.017 (0.030)	0.026 (0.027)	0.027 (0.027)
Belgium		0.147 (0.124)	0.248* (0.113)	0.255* (0.115)
France		0.173*** (0.050)	0.209*** (0.046)	0.215*** (0.046)
Great Britain		0.442+ (0.243)	0.333 (0.222)	0.333 (0.223)
Luxembourg		0.395 (0.243)	0.533* (0.222)	0.539* (0.224)
Netherlands		0.145*** (0.039)	0.163*** (0.036)	0.162*** (0.036)
Poland		0.242*** (0.052)	0.251*** (0.047)	0.250*** (0.047)
Other countries		0.047 (0.243)	-0.045 (0.222)	-0.061 (0.222)
Year (ref: 2018)				
Year 2019			0.062* (0.027)	0.075* (0.031)
Year 2020			0.188*** (0.028)	0.195*** (0.032)
Year 2021			0.264*** (0.029)	0.295*** (0.034)
Year 2022			0.288*** (0.029)	0.300*** (0.037)
Year 2023			0.243*** (0.044)	0.207*** (0.057)
Green building x 2019				-0.066 (0.068)
Green building x 2020				-0.047 (0.070)
Green building x 2021				-0.107 (0.068)
Green building x 2022				-0.060 (0.067)
Green building x 2023				0.049 (0.097)
Num.obs.	728	728	728	728
R^2	0.609	0.630	0.696	0.698
R^2 adj.	0.595	0.611	0.678	0.678
AIC	38.4	21.7	-111.9	-106.8
BIC	157.7	196.1	85.5	113.5
RMSE	0.24	0.23	0.21	0.21
Regional effects	N	Y	Y	Y
Time effects	N	N	Y	Y

Note: The standard errors are indicated in parentheses. The levels of statistical significance are represented as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models are estimated using heteroskedasticity-robust covariance matrix estimators. The variable green building is a dummy variable that is one if the respective asset is classified as a green building by the lender, according to the classification described in the text. The categorical variables for investor profile describe the classification of the type of investor made by the lender and is independent of the financed asset. The variable customer rating describes the risk classification of the customer made by the lender, where 1 = least risky and 5 = most risky, and is also independent of the asset. The year refers to the year of financing issuance. The interaction term between year and green building is one if a financed asset was classified as green in the respective years.

Central to our research question is a significant green building dummy variable in Model 3, which indicates a green discount in the lender's target spreads. With a coefficient of -0.040 or -3.92%, and taking into account the average loan size and the average target spreads in our sample, we can observe a discount of approximately 5 bps, which translates into interest savings of €20,776 in the first year. In this context, it is crucial to note that the green discount is comparatively lower in the lender's internal calculations than in the contracted spreads. This distinction promotes a nuanced understanding of the green discount from both the lender's and the borrower's perspective. As for the *LogSpread*, it can be observed that the interaction term between the year and the green building variable in Model 4 does not exert a significant influence on the *LogTargetSpread* and suggests an increase in multicollinearity.

We attribute the green discount in loan spreads to two potential drivers. One perspective is that lenders perceive a reduced risk associated with green properties, as suggested by previous research from An and Pivo (2020) and Devine and Yönder (2021). The lower default risk of green properties identified by An and Pivo (2020) is primarily reflected in the specific risk component of the spread. A green premium in the income component of properties has been extensively documented in the literature. It translates into improved operational performance and higher NOI. This risk consideration holds significant importance for lenders, given that a higher NOI correspondingly improves the property's debt service coverage ratio (DSCR), ensuring the property's capacity to meet fixed debt obligations encompassing both principal and interest payments. The presence of a green premium in property values also result in less collateral risk for lenders. A lower exposure to transition risks could further reduce the collateral risk of green properties. Unlike voluntary commercial certifications, the actual energy intensity of properties not only mirrors a current market standard that positively affects the property's marketability but also potentially poses an ongoing and future risk to the property's cash flow. This risk emanates from two principal factors: firstly, the costs for fossil energy sources are expected to continue rising; secondly, consumption levels exceeding regulatory thresholds will likely be subject to a carbon pricing mechanism. As previously mentioned, only a specific portion of the total energy consumption in the real estate sector can be met through renewable energy sources in the foreseeable future. This scenario underscores the critical need for enhancing energy efficiency and incorporating the gradual elimination of fossil fuels into asset management and development strategies. Looking ahead, the implementation of these measures is likely to be more about averting financial losses than about achieving actual value increases. This proactive approach is essential not only for sustainability but also for safeguarding the long-term financial viability and resilience of assets in an increasingly environmentally-conscious market. The importance for lenders of incorporating these transition risk drivers into their risk considerations is also evident in other sectors of the economy (Chava, 2014; Krueger et al., 2020; Bolton & Kacperczyk, 2021). With regard to the systematic risks, Geltner (1989) and Naranjo and Ling (1997) emphasize the risk premium resulting from the comovement between economic consumption and property performance. If lenders assume green properties to have lower correlation with general economic demand, driven by factors such as regulatory support, higher tenant demand, or cost efficiencies, this might also lead to a green discount within the systematic risk component of spreads.

Growing regulatory requirements and the impact of internal and external stakeholders on climate goals in the banking industry are adding a new dimension to the concept of a green discount. Although EU taxonomy does not require a specific minimum GAR, and several other economies have not yet adopted mandatory reporting of such ratios, the proportion of green real estate is having an increasingly significant impact on transparency and comparability of lenders' portfolios. This may result in increased tensions among management, stakeholders, and shareholders with respect to a sustainability strategy on one hand, and the financial implications of reputational harm and liability concerns stemming from greenwashing or even detrimental environmental effects on the other (Brühl, 2023). In addition to the conventional components of the spread mentioned above, lenders may intentionally price in a green component that gives them room for negotiation in the loan origination process. Permitting a green discount, as evidenced by our findings, could facilitate the origination of green loans and consequently increase the share of green properties in the lenders' loan portfolios. As shown in Figure 5.5, the proportion of capital made available for green loans has been steadily increasing over recent years. While the green discount may factor into internal spread calculations, there is currently no evidence of any commercial lender in the European market actively offering such finance concessions. Regarding the US market this observation is also noted by Mathew et al. (2021).

The distinction between the target spread and the contracted spread in our analysis provides a valuable framework for evaluating the green discount from both the lender's and borrower's perspectives. Under the previously established hypothesis that lenders deliberately price a green component into spreads, the green discount in the target spread can be understood as the internal value that lenders associate with the origination of green loans. Assuming economic rationality, lenders will seek to minimize the green discount. Hence, the difference between the green discount within the target spread and the contracted spread may be interpreted as an indicator of how the supply side of green buildings perceives its bargaining position during loan origination. As shown in Tables 5.2 and 5.3, the comparison of both regressions in Model 3 indicates that the green discount is 36% higher for contracted spreads. Even though the difference of approximately 2 basis points between the two is negligible from an economic standpoint, it signifies that lenders are required to offer a marginally higher green discount in loan origination than their initial calculations indicate. With regard to borrowers holding green properties, our results suggest that they are conscious of their leverage and pursue the greatest possible green discount.

Table 5.4 presents the regression results for the dependent variable LTV. Model 3 again has the best fit and is used as the basis for interpreting the coefficients. However, the model only achieves an adjusted R^2 of 0.379, which is significantly lower than in the (target) spread analysis. We attribute this lower explanatory power to the fact that, unlike spreads, the absolute level of the LTV depends not only on property- and borrower-specific factors, but also on exogenous drivers that are not captured by the model.

Table 5.4: Hedonic Model Results where $y = LTV$ (in %)

Model	1	2	3	4
(Intercept)	67.100*** (2.012)	66.332*** (2.135)	70.669*** (2.346)	71.099*** (2.428)
Green building	-0.016 (1.134)	0.058 (1.149)	1.123 (1.184)	-1.795 (3.335)
LogMargin	4.039* (2.052)	4.683* (2.094)	8.339*** (2.271)	8.525*** (2.278)
Volume (in t. €)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Maturity (in months)	-0.038** (0.014)	-0.033* (0.014)	-0.038** (0.014)	-0.037** (0.014)
Investor profile (ref: developer)				
Fund	-13.461*** (2.855)	-14.171*** (2.928)	-11.930*** (2.940)	-11.779*** (2.943)
Foreign investor	-16.561*** (1.572)	-13.930*** (2.067)	-12.115*** (2.099)	-12.170*** (2.106)
Domestic investor	-8.995*** (1.680)	-9.301*** (1.695)	-8.214*** (1.700)	-8.205*** (1.703)
Investment management	-19.822*** (2.271)	-20.272*** (2.339)	-18.333*** (2.354)	-18.348*** (2.360)
Housing company	-3.207 (2.802)	-3.833 (2.927)	-1.863 (2.961)	-1.645 (2.982)
Customer rating (ref: 1)				
Customer rating 2	3.342* (1.527)	3.423* (1.535)	2.306 (1.540)	2.254 (1.544)
Customer rating 3	8.061*** (1.760)	7.947*** (1.765)	6.292*** (1.790)	6.267*** (1.799)
Customer rating 4	11.396*** (2.158)	11.514*** (2.164)	9.533*** (2.193)	9.478*** (2.200)
Customer rating 5	15.812** (5.081)	14.874** (5.077)	12.090* (5.054)	12.294* (5.064)
Property type (ref: office)				
Retail	2.229 (1.800)	0.788 (1.889)	0.668 (1.869)	0.615 (1.877)
Specialty retail centers	6.609 (4.345)	5.177 (4.429)	7.107 (4.418)	7.590+ (4.437)
Hotel	-6.638 (6.109)	-5.923 (6.095)	-5.716 (6.038)	-5.986 (6.056)
Department store	-2.798 (6.057)	-2.330 (6.155)	-0.711 (6.135)	-0.027 (6.169)
Logistics	-3.071+ (1.692)	-4.843** (1.821)	-4.148* (1.807)	-4.034* (1.821)
Management properties	-1.772 (3.575)	-2.755 (3.570)	-2.888 (3.536)	-3.238 (3.546)
Parking garage	1.988 (6.915)	5.036 (7.037)	5.902 (7.024)	7.291 (7.075)
Mall	-1.126 (7.816)	-2.734 (7.861)	0.095 (7.842)	1.173 (7.906)
Residential investment	2.233 (1.364)	2.204 (1.384)	3.347* (1.400)	3.455* (1.407)
Social property	0.294 (9.659)	-1.439 (9.628)	-1.542 (9.550)	-2.049 (9.565)
Other	11.167* (4.593)	10.337* (4.585)	10.635* (4.563)	10.869* (4.589)
Region (ref: DE: old states A-cities)				
DE: old states B-cities		4.140* (1.836)	3.944* (1.823)	3.853* (1.836)
DE: old states (other)		3.370+ (1.801)	2.254 (1.809)	2.201 (1.823)
DE: new states B-cities		0.278 (2.939)	-0.190 (2.913)	-0.589 (2.923)
DE: new states (other)		2.285 (3.141)	1.958 (3.125)	1.809 (3.139)
DE: Berlin		-1.490 (1.636)	-1.882 (1.622)	-1.982 (1.627)
Belgium		-4.201 (6.825)	-6.266 (6.807)	-5.438 (6.919)
France		-3.549 (2.802)	-4.977+ (2.793)	-5.257+ (2.803)
Great Britain		-11.876 (13.435)	-11.851 (13.308)	-9.877 (13.369)

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Table 5.4: Hedonic Model Results where $y = LTV$ (in %) (Continued)

Luxembourg		20.682 (13.431)	17.093 (13.353)	18.140 (13.460)
Netherlands		-3.439 (2.182)	-4.302* (2.172)	-4.111+ (2.196)
Poland		-2.007 (2.901)	-3.079 (2.887)	-2.844 (2.904)
Other countries		-0.025 (13.415)	0.654 (13.298)	1.266 (13.326)
Year (ref: 2018)				
Year 2019			-4.152* (1.633)	-4.231* (1.844)
Year 2020			-6.817*** (1.722)	-6.882*** (1.937)
Year 2021			-6.464*** (1.820)	-7.756*** (2.147)
Year 2022			-6.921*** (1.870)	-9.338*** (2.293)
Year 2023			-8.508** (2.695)	-8.035* (3.410)
Green building x 2019				1.403 (4.078)
Green building x 2020				1.030 (4.174)
Green building x 2021				4.650 (4.067)
Green building x 2022				6.287 (4.008)
Green building x 2023				0.391 (5.796)
Num.obs.	728	728	728	728
R^2	0.377	0.396	0.414	0.418
R^2 adj.	0.356	0.364	0.379	0.379
AIC	5852.0	5854.1	5841.5	5846.5
BIC	5971.3	6028.5	6038.8	6066.8
RMSE	13.07	12.87	12.67	12.63
Regional effects	N	Y	Y	Y
Time effects	N	N	Y	Y

Note: The standard errors are indicated in parentheses. The levels of statistical significance are represented as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All models are estimated using heteroskedasticity-robust covariance matrix estimators. The variable green building is a dummy variable that is one if the respective asset is classified as a green building by the lender, according to the classification described in the text. The categorical variables for investor profile describe the classification of the type of investor made by the lender and is independent of the financed asset. The variable customer rating describes the risk classification of the customer made by the lender, where 1 = least risky and 5 = most risky, and is also independent of the asset. The year refers to the year of financing issuance. The interaction term between year and green building is one if a financed asset was classified as green in the respective years.

With a statistically significant coefficient of 8.339, the spread variable has a positive impact on the LTV. This observation is consistent with the results of the models with *LogSpread* and *LogTargetSpread* as dependent variables, where the LTV coefficient is consistently positive and significant. However, the interaction is marginal and holds relatively little importance in the overall context. Our results align with the findings of Titman et al. (2005) who attribute the weak link between LTV and spreads to the fact that the LTV is determined endogenously. Factors such as negotiations between lenders and borrowers may have an impact on the final LTV choice. The coefficients further indicate that the term to maturity has only limited impact on LTV ratios.

The analysis of the coefficients of the investor profile variables shows that the reference category developer has the highest LTV, while the other variables are associated with negative coefficients. This is in line with our initial hypothesis that developers are constrained by their equity capital and have to rely heavily on debt capital. In contrast, investment managers have the largest negative coefficient at -18.333, which is expected since they typically execute equity investments for their clients with a limited amount of debt. However, the results for customer ratings are not straightforward to interpret. Similar to the spread models, higher risk ratings are associated with higher average LTVs. This could be attributed, on the one hand, to the risk-return profile of the lender and, on the other hand, to the fact that the types of investors involved in highly leveraged projects generally represent a higher risk for banks at the corporate level.

Looking at the different property types in our analysis, there is no significant effect on the LTV, except for the coefficients of logistics and residential properties. In contrast to the office reference category, the residential category exerts a positive influence on the LTV. Consequently, residential properties within our sample tend to secure higher LTVs, assuming all other factors being equal. This implies that lenders perceive residential properties as less risky when compared to office properties. Additionally, consistent with the results from spread models, promotional loans for residential properties may enable higher LTV ratios at lower spreads. The lender's approach appears to be different for properties in the Netherlands. Compared to the reference category Germany: old states A-cities, the Netherlands dummy results in a spread premium and a negative LTV adjustment of -4.302, indicating a more conservative lending approach.

The time effects introduced in Model 3, using 2018 as the reference year, consistently show significant negative values and lead to an improvement in the adjusted R^2 compared to Model 2. While loans had higher LTV ratios on average in 2018, there is a modest downward trend up to and including 2023. This observation is in line with a European-wide trend in recent years, according to which the LTV ratios for commercial real estate have declined on average (European Central Bank, 2023).

Unlike the green discount observed in credit spreads, none of our models with LTV as the dependent variable indicates a significant influence from the green building coefficient. As with the other models in our analysis, the interaction terms in Model 4 fail to enhance the goodness of fit and lack statistical significance. A further descriptive analysis of our dataset with a focus on developers does not reveal any difference in LTVs between green and non-green projects. Given the market barriers and market failures highlighted by Chegut et al. (2019), our findings suggest that green properties and especially green development projects are not incentivized with additional loan proceeds. As a result, developers are unable to secure extra senior debt to cover shortages in capital during the initial stages of green construction projects, which involve higher upfront costs and extended construction timelines. Instead, they must seek alternative financing, such as additional equity or mezzanine capital, thus leaving market barriers for developers of green buildings in place. However, findings by Chegut et al. (2019) also reveal that the marginal costs associated with green construction projects are offset by the green value premium they achieve after completion. The lack of statistical significance of the green variable in our sample may, therefore, be explained by the fact that investing in properties or financing green projects after their completion does not specifically require more debt capital compared to their non-green peers due to the value premium they achieve.

5.6 Conclusions

Despite the robustness of our statistical models and the high quality of the data utilized, there are some limitations in interpreting the results of any hedonic model. A primary limitation is the challenge of completely controlling for endogeneity issues between green and non-green properties, even with the application of comprehensive control variables. Incorporating cash flow-related metrics like the DSCR into the existing dataset could significantly mitigate potential biases in loan risk assessment, thereby enhancing the overall robustness of the results. Furthermore, it is important to note that the dataset is representative of a specific sample, confined to a particular period and region. Consequently, the insights derived from this dataset may not be universally extendable to all commercial real estate lenders.

Our study emphasizes that the assessment of a property's environmental performance has become an integral part of loan origination for lenders in the commercial real estate sector. Due to the rise in regulations, such as EU taxonomy, lenders are expanding their assessment criteria beyond commercial certification schemes and are placing greater emphasis on the actual energy efficiency of buildings. At the same time, this implies that borrowers have to meet more stringent property standards in order to qualify for a green loan.

Although confirming previous research that finance concessions associated with green properties are not publicly offered by commercial lenders, our findings still provide evidence for a green discount in loan spreads. Applying a hedonic regression analysis while accounting for both observed and unobserved heterogeneity in loan data, we identified a reduction of 3.92% in lender's target spreads for green properties and 5.35% in contract spreads, respectively. The size of the green discount is consistent with previous findings for the U.S. market. This reduction seems to remain constant throughout the observed timeframe, without any statistically notable changes in the green discount across the years. We attribute the green discount to two potential drivers. Firstly, lenders perceive lower risk associated with green properties, which has a positive impact on the risk components in spreads. Secondly, lenders provide some leeway for negotiation within the commission spreads during the loan origination process, allowing them both to incentivize green loans and thus to increase their own green asset ratio. The spread of the green discount between the calculated target spread and the contractually agreed spread can be interpreted as the deviation between the internal value that lenders place on green loans and the bargaining power of borrowers holding green properties. In light of the economically marginal spread of approximately 2 basis points, borrowers align with lenders' perceptions of fair market conditions. However, the supply side of green buildings is well aware of its bargaining power, pushing lenders to grant a slightly higher green discount than their internal calculations indicate.

While incentives for borrowers are already reflected in lower spreads, our examination does not indicate higher LTV ratios for green properties, leading to additional loan proceeds for borrowers. As a result, lenders are not fully addressing the potential shortage of capital on the supply side, stemming from the higher up-front costs and and extended construction timelines associated with green buildings, by providing additional debt capital. Furthermore, banks are forced to further improve their own green asset ratio in the face of new regulations and net zero targets. Our sample highlights a gradual greening of lenders' portfolios in recent years, yet opportunities for improvement still remain. Introducing stronger incentives for the supply side of green buildings is one way to increase this ratio in the future, simultaneously stimulating more green construction and retrofits. Future research may show whether lenders globally are adopting a comprehensive green discount, thereby contributing to the elimination of market inefficiencies and promoting the adoption of energy efficient buildings, as suggested by the green premium observed on the equity side of real estate.

5.7 Appendix

Table 5.5: Results of Variance Inflation Factor Models where $y = LogSpread$

Model	Variable	$GVIF$	Df	$GVIF^{(1/(2*Df))}$
Model 1	Investor profile	4.322232	6	1.129733
	Customer rating	2.199901	8	1.05051
	Property type	2.334517	11	1.039289
	Green building	1.166907	1	1.080235
	LTV (in %)	1.636945	1	1.279432
	Volume (in t. €)	1.091463	1	1.044731
	Maturity (in months)	1.576548	1	1.255606
Model 2	Investor profile	10.138731	6	1.212919
	Customer rating	2.641558	8	1.062591
	Property type	3.825711	11	1.062887
	Green building	1.2155	1	1.102497
	LTV (in %)	1.693176	1	1.301221
	Volume (in t. €)	1.133989	1	1.064889
	Maturity (in months)	1.654996	1	1.286466
	Region	6.306539	12	1.079754
Model 3	Investor profile	10.848957	6	1.219782
	Customer rating	2.819923	8	1.06694
	Property type	4.422519	11	1.069913
	Green building	1.3162	1	1.147257
	LTV (in %)	1.727224	1	1.314239
	Volume (in t. €)	1.138377	1	1.066947
	Maturity (in months)	1.715995	1	1.30996
	Region	7.200627	12	1.085735
	Year	1.708522	5	1.055023
Model 4	Investor profile	11.322948	6	1.224137
	Customer rating	2.983629	8	1.070709
	Property type	4.840777	11	1.074317
	Green building	10.521224	1	3.243644
	LTV (in %)	1.735328	1	1.317318
	Volume (in t. €)	1.147941	1	1.07142
	Maturity (in months)	1.729108	1	1.314956
	Region	8.316685	12	1.092273
	Year	15.46262	5	1.315008
	Green building x year	100.797984	5	1.586153

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6 Concluding Remarks

The effects of climate change on asset classes and their implications for financial stability have become central themes in economic discussions. Research on climate-related asset devaluations, capital reallocation and the widening climate finance gap highlights the need to incorporate climate risks into both strategic planning and regulatory frameworks. In this context, this dissertation aimed to examine how climate-related risks—categorized as *physical*, *transition* and *liability risks*—affect the real estate asset class, and what these risks mean for investor and lender strategies. This analysis drew on the combined findings of four individual articles.

Although the impact of *physical risks* on real estate markets is well-documented, this dissertation contributes to a less-developed area of research. By identifying a significant negative relationship between spatial UHI effects and residential property prices, it demonstrates that the economic impact of *physical risks* extends beyond immediate hazards like floods and wildfires. Gradual, less-visible risks—such as rising temperatures in urban areas—also shape real estate valuation, despite being harder to quantify. The findings suggest that risks to human health, building performance and the livability of urban environments are increasingly priced into real estate markets. Investment managers and lenders who focus solely on acute natural hazards in their risk assessments may be underestimating their overall exposure. Economic losses tied to *physical risks* like UHI effects—unlike building losses—are virtually uninsurable. As a result, their financial relevance will only grow, making them a critical consideration in climate risk management strategies.

When effectively integrated into investment strategies, comprehensive climate risk management can help prevent financial losses and uncover new sources of value. Our findings show that rooftop solar potential is a significant driver of firm value for REITs, highlighting the role of on-site renewable energy in mitigating *transition risks*. By supporting the shift to electrified building systems and reducing reliance on expensive, fossil-fuel-based energy, these strategies strengthen firms' resilience to changing market conditions. Our observations further emphasize that REITs with properties tied to more carbon-intensive power grids are valued at a discount. In addition to lowering exposure to transition risks, on-site renewable energy generation offers an opportunity to create new revenue streams. While this research focuses on rooftop solar, the findings may also apply to other decentralized energy sources, such as waste heat recovery or small-scale hydroelectric power for water-adjacent properties. As such, a thorough assessment of a portfolio's renewable energy potential could be financially prudent—both to manage *transition risks* and to unlock untapped value.

The regulatory landscape itself presents a growing *transition risk* for the real estate sector. This dissertation, using the SFDR as a reference point, highlights the shortcomings of one-size-fits-all policies, especially for alternative asset classes like real estate. It calls for regulatory frameworks that reflect the sector's specific characteristics. While our results indicate an initial return premium for real estate funds in higher SFDR categories, this should not be the sole driver of investment strategy. Instead, managers should anticipate future regulatory changes and consider aligning their fund launches with lower SFDR categories when appropriate. Doing so may help avoid costly downgrades later and encourage the implementation of transition strategies in less sustainable property portfolios.

Finally, this dissertation indicates that lenders, too, are beginning to incorporate climate-related risks into their financing decisions. As banks under the EU taxonomy seek to improve their GAR, those that fail to align with decarbonization goals face increasing exposure to *transition* and *liability risks*, including reputational damage and the potential for litigation tied to environmentally harmful lending. Beyond corporate- or management-level assessments, banks must also account for climate risks at the property level to avoid collateral-related losses. Our findings reinforce this need, showing that loans for greener properties benefit from a measurable 'green discount' in interest rates. However, similar to the challenges observed with the SFDR, the EU Taxonomy has not yet fulfilled its intended purpose in the banking sector. Rather than directing capital into the decarbonization of carbon-intensive existing buildings, it tends to favor assets that are already green—thereby widening the climate finance gap.

Taken together, these findings provide a deeper understanding of how climate-related risks influence economic outcomes within the real estate asset class. While academic interest in this topic has grown, research into sector-specific and risk-specific dynamics remains limited. Given the increasing severity of physical climate hazards, rising investor expectations and rapidly evolving regulations, this study captures only a snapshot in a fast-changing market. Continued research will be critical to support strategic decision-making by management, policy makers and financial regulators alike.