Essays on Modeling Extreme Loss
Risk for REITs and Evaluating
Green Retrofit Measures

Dissertation zur Erlangung des Grades eines
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vorgelegt von: Alexander Michael Groh

Berichterstatter: Prof. Dr. Sven Bienert
Prof. Dr. Tobias Just

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Dissertation
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Alexander Michael Groh

Erstgutachter:	Prof. Dr. Sven Bienert MRICS REV
Zweitgutachter:	Prof. Dr. Tobias Just FRICS
Dekan:	Prof. Dr. Klaus Röder
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1. Introduction

1.1 Background and Motivation

The years during which the present dissertation has been written, are ones that will be remembered for a long time. While the COVID-19 pandemic had an enormous impact, 2019 to 2022 brought many more and different challenges. There included wildfires in Australia, North America and Europe, followed by a long list of devastating hurricanes and catastrophic floods, even in areas previously considered safe from such incidents (Eckstein, Künzel, & Schäfer, 2021; World Economic Forum, 2022). But not only natural disaster struck, also widespread social unrest in the US and a raging war in Ukraine highlighted the reality of persistent, disruptive volatility. Such risk factors are likely to increase in the future due to environmental, demographic, and socioeconomic changes (Sharma et al., 2022) and will threaten existing business models in all social and economic areas – including, of course, real estate – and force them to adapt. While no individual or organization is able to accurately predict specific risks factors, there is a need for companies to monitor and evaluate them and implement strategies to face future uncertainties. For real estate, these threats include pandemics, climate change, changing demographics, changes in tenant preferences, geopolitical risks, issues relating to global supply chains, changes in technology, and factors that are simply unknown and unpredictable at the moment (Clayton et al., 2021).

Climate change, as one of the main if not the dominant challenge of present generations has reached high levels of public awareness in recent years. Real estate companies, especially listed ones, have the fiduciary duty to protect the value of the portfolios under their management and to address and mitigate any financial uncertainties associated with climate change. There are two different forms of risk related to climate change that need to be considered for real estate management, namely: Direct Physical Risk and indirect Transition Risk (Vrensen et al., 2020). Physical climate risk refers to natural disasters or extreme weather events like wildfires, floods, or storms, but also to gradual changes in temperature and precipitation that might directly damage buildings or decrease building value by increasing maintenance and/or insurance costs (Hirsch, Braun, & Bienert, 2015; Absolut Research, 2019). Transition climate risk refers to regulatory changes associated with the transformation towards sustainable development, which might cause an asset to become “stranded” (Hirsch, Spanner, & Bienert, 2019). The term "stranded assets" originated in the context of companies in the coal or oil industry and suggests that some resources currently considered in company valuations should be re-evaluated if, for example, demand for these resources is expected to decline, or if producers must bear a (carbon) tax (Caldecott, 2018a; Caldecott, 2018b). In the context of the real estate industry, assets are called "stranded" if they do not meet regulatory requirements and market expectations in terms of carbon footprint or it is foreseeable that they will not meet them in the future (Caldecott et al., 2017; Hirsch, Spanner, & Bienert, 2019). If such requirements are not met, costs due to the pricing-in of carbon emissions (e.g., through taxes), technological disruptions, legal liabilities, and reputational risks – all of which could potentially reduce property values – can be expected. To avoid the stranding of an existing building, the owner needs to invest in green retrofit measures.[1] The term “retrofit” in general refers to the modernization or expansion of existing (usually older) plants and equipment. In the real estate context, the US Green Building Council (USGBC) defines a green retrofit as *“an upgrade at an existing building to improve energy and environmental performance, reduce water use, improve comfort and quality of space in terms of natural lighting, air quality and noise”* (USGBC, 2009). This includes, but is not limited to, improving the energy efficiency of heating, lighting, cooling, ventilation, and other mechanical systems, increasing the quality of insulation in the building envelope, implementing sustainable energy generation, but also aiming to improve occupant comfort and health. Two of the three research articles included in the present thesis go into more detail on the micro and macroeconomic implications of green retrofits.

Research Article 1 *"The Value Effects of Green Retrofits"*, of this cumulative dissertation, focuses on describing and analyzing the impact of retrofits on property values and analyzing its components, whereby three types of value effects are described. Namely, the value impact of the capitalization of energy savings, lower value discounts due to stricter standards (reduced transition risk) and the value uplift due to indirect benefits (health, employee satisfaction, marketing, etc.) are identified, visualized in a stylized example, and exemplified in a brief empirical analysis. Nevertheless, the article is theoretical in nature and in terms of investigating green premia (value increases due to green features).

While Articles 1 and 3 are thematically closely related, as both revolve around economical considerations regarding green retrofits, Article 2 *"Multivariate Tail Risk Modeling for REITs: What Factors Drive Extreme Losses?"* is distinct from the other two in terms of subject matter. It is a clear contribution to the risk management literature in real estate investing and within it, belongs to the literature strand of Extreme Value Theory (EVT). While the traditional mean-variance theory focuses on a log-normal distribution and measures risk by the standard deviation of returns, the EVT is the study of the tail of the return distribution. In financial markets, extreme price movements correspond to market function during ordinary periods, and also to stock market crashes, real estate market collapses, financial/currency crises and other highly volatile periods which are connected with an extreme event (Liow, 2008). The research objective of Paper 2 is to implement a novel methodology motivated by Chavez-Demoulin, Embrechts & Hofert (2016), in order to model extreme loss observations for Real Estate Investment Trusts (REITs). The study

[1] Note that in general, the stranding of a building could also be avoided by demolishing it (and rebuilding it), but on a macroeconomic level, this cannot be the regular case as a means of meeting net zero carbon emissions by 2050 or even 2045. With the low rate of new construction in Germany (and Europe) of approximately 0.7%, the outdated share of the building stock cannot merely be replaced within the remaining time (Destatis, 2021). Moreover, demolition and new construction lead to higher footprints in terms of embodied carbon (ifeu, 2021).

examines whether exogenous market covariates provide explanatory power for the estimation of Generalized Pareto Distributions (GPD) in a non-linear generalized additive model framework, which is more flexible than classic Gaussian approaches (Danielsson & de Vries, 1997). The main finding from this unique and methodology-driven approach to REIT returns is that a superior model fit is present, due to the inclusion of covariates for estimating the GPD's moments. The results both enhance our understanding of the employed covariates from an academic perspective, and are also of value from a practical point of view. For the financial risk management of a portfolio containing multiple assets, it is crucial to understand the joint behavior of the assets, besides the marginal behavior of each individual asset. The EVT-based methodology for studying the dynamics of tail behavior is capable of increasing portfolio performance in times of crisis and can guide risk management measures with respect to corresponding factors like market interest rates, stock index returns or term structure.

Research Article 3, *"Does retrofitting pay off? An analysis of German multifamily building data"* builds thematically on Article 1 and addresses the question of whether a retrofit pays off financially from a landlord's perspective. This question arises, because landlords do not benefit directly from all the value effects of retrofits, but must bear the full cost. The conducted marginal analysis of green retrofits is critical, because it adds to our understanding of why renovation rates are remaining at low levels, despite continued regulatory efforts to increase them. To quantify it's current regulatory incentive effect, the marginal cost analysis in broadened by including the still young CO_2 taxation for fossil fuels consumed on site in Germany and the newly introduced split allocation of the CO_2 price between tenants and landlords. This study is strongly data-driven and uses a unique and difficult-to-acquire dataset for Germany regarding retrofit costs of multifamily buildings. The findings suggest that, on average and under current conditions, retrofits are economically disadvantageous for landlords, without the addition of public subsidies.

The present thesis extends the real estate literature by exploring extreme loss risk factors of REITs and the economics of green retrofit measures in an analytical, systematic, and critical manner. The results on the one hand aim to provide a new framework for rendering modern real estate risk management more resilient to extreme risks. On the other hand, the dissertation provides insights into practice-relevant climate risk mitigation.

The remainder of the thesis is structured as follows. In the following section, the research questions of the three papers are explicitly and concisely listed, and the subsequent section identifies co-authors, submission status, and previous as well as future conference presentations. In chapters 2, 3 and 4, the three research articles of the dissertation are reproduced in the version submitted to or published in the respective journals. At the beginning of each of these chapters, you will find the abstract of the article and up to eight keywords. Since the journals have different guidelines regarding the form of the abstract (structured/unstructured), they differ in this respect. The last chapter contains the conclusion starting with an Executive Summary of the articles, then the concluding answers to the derived research questions, research limitations, and an outlook for potential future research.

1.2 Research Questions

This section provides a brief overview of the research questions relevant for each of the three research articles.

Paper 1 | The Value Effects of Green Retrofits

- How do energy efficiency gains affect the value and valuation of properties?

- To what extent will future policy measures affect current property prices?

- How does a deep retrofit with energy efficiency improvement add value to a property?

- What is the magnitude of these value effects?

Paper 2 | Multivariate Tail Risk Modeling for REITs: What Factors Drive Extreme Losses?

- Does econometric modeling of the extreme losses of securitized real estate investments provide any insights compared to the current methods for risk assessment?

- What exogenous risk factors yield explanatory power to describe the excesses located in the lower tail of REIT return distributions?

- Are the extreme value losses more strongly driven by equity market or debt market covariates and do the respective strengths of the influences differ with regard to the REIT asset class under consideration?

Paper 3 | Does Retrofitting Pay Off? An Analysis of German Multifamily Building Data

- Is there a green premium in the rental market for multifamily units in Germany?

- Provided that a price premium is indeed found, is the rent increase potential from an improvement in energy efficiency sufficient to offset the costs of a retrofit, over the expected useful life of the asset?

- Does the level and design of the CO_2 tax on fossil fuels for residential heating provide a sufficiently strong incentive for owners of energetically poor multi-family houses to retrofit their properties for energy efficiency?

1.3 Co-Authors, Submissions and Conference Presentations

In the following, information on co-authors, journal submissions, publication status and conference presentations for each of the three papers is provided.

Paper 1 | The Value Effects of Green Retrofits

Authors:

Dirk Brunen, Alexander Groh & Martin Haran

Submission Details:

Journal:	Journal of European Real Estate Research (JERER)
Submission date:	12/02/2019
Current status:	Published
Publication date:	09/24/2020
DOI:	https://dx.doi.org/10.1108/JERER-12-2019-0049

Paper 2 | Multivariate Tail Risk Modeling for REITs: What Factors Drive Extreme Losses?

Authors:

Cay Oertel & Alexander Groh

Submission Details:

Journal:	Real Estate Finance (REF)
Submission date:	07/24/2021
Current status:	Accepted

Conference Presentations:

This paper was presented over Zoom at the hybrid 27th Annual Conference of the European Real Estate Society (ERES) in Kaiserslautern, Germany (2021).

Paper 3 | Does retrofitting pay off? An analysis of German multifamily building data

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Authors:
Alexander Groh, Hunter Kuhlwein & Sven Bienert

Submission Details (1):

Conference Proceedings:	IOP Conference Series: Earth and Environmental Science
Submission date:	03/14/2022
Current status:	Accepted

Submission Details (2):

Journal:	Journal of Sustainable Real Estate (JOSRE)
Submission date:	05/03/2022
Current status:	Under Review

Conference Presentations:

This paper will be presented at the Sustainable Built Environment D-A-C-H Conference 2022 (sbe22), which will take place from 20th till 23rd September 2022 in Berlin. A short version of the Paper will be printed in the related conference proceedings.

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2. The Value Effects of Green Retrofits

2.1 Abstract

Purpose: This paper aims to decompose the value effects of green retrofits on commercial real estate. The paper disentangles various sources of value capture mechanisms that can be attained through green retrofit actions and profiles the extent to which green retrofit solutions can be effectively capitalised using transaction evidence from the Munich housing market. The insights offered can help real estate owners and investors during their ex ante analysis of future energetic retrofit investments.

Design/methodology/approach: The authors offer their reader both a conceptual framework and the results from an empirical analysis to identify the value effects of retrofits and the associating gains in energy efficiency. The conceptual framework theorises the different value components that a deep retrofit has to offer. The regression analysis includes a multivariate analysis of 8,928 dwellings in the Munich residential real estate market.

Findings: This study's framework disentangles the total retrofit value effect into three components: the capitalisation of energy savings, the exposure to the value discount because of stricter standards and the value uplift because of indirect benefits (health, employee satisfaction, marketing etc.). The regression results indicate that the value gains because of energy efficiency improvements are in the range of 2.4–7.4%, while the indirect benefits and reduced exposure to stricter standards amount to another 3%.

Originality/value: While numerous studies have investigated the upside value effects of energy efficiency in the real estate sector, there is scant academic research which has sought to evidence the value of green retrofit solutions and the extent to which this can be capitalised. Instrumentalising the various value effects of energetic retrofit that have been identified is not straightforward. At the same time, inadequate value capture of energetic retrofit effects could delay intervention timelines or aborting of proposed retrofit actions which should be of primary concern to policymakers and stakeholders tasked with the decarbonisation of real estate assets.

Key Words: Energy performance certificates, Green premia, Multivariate regressions, Munich house prices, Energy efficiency, Retrofits, Value effect

2.2 Introduction

In June 2000, the European Climate Change Program (ECCP) was launched by the European Commission to avoid the harmful effects of climate change. The ECCP identified, developed and incorporated the necessary elements of a European strategy to implement the Kyoto Protocol. New policy directives have been issued to guide all industries towards the 2050 aim of an 80% carbon reduction. As the real estate industry is accountable for almost 30% of all greenhouse gas (GHG) emissions in the European Union (EU) (IPE 2018), the real estate sector plays a pivotal role in the EU decarbonisation efforts stated in the Intended Nationally Determined Contributions. To optimise the potential contribution of the real estate sector, there is a pertinent need for stricter building codes for energy efficient new construction as well as more robust measurement and assessment of embodied carbon across the various stages of the asset life cycle. The most impactful benefits nonetheless will be realised through the upscaling of green retrofit solutions and for targeted intervention to facilitate and enable reductions in the carbon intensity of existing buildings. Ambitious retrofit policies and robust decarbonisation pathways can help reduce real estate's carbon footprint by up to 46% between 2021 and 2030 (European Commission, 2014). Nonetheless, while deep energy retrofits can appear profitable on paper, not just from a climate change perspective, they occur only occasionally in the market.

In theory, these green retrofits should lead to three value effects. Given that these retrofits are undertaken and calibrated to reduce energy use (and costs), a first source of value effects should be the capitalisation of future energy cost savings. As long as the net present value of future energy costs savings exceeds the immediate retrofit investment, we expect a proportional "green" premium of the property right after the retrofit is finalised. In the case of owner-occupiers, the outlook of lower energy costs will directly be included in the budget of the users' lifecycle costs. In the case of properties that are leased to tenants, the same value effect should appear as long as rents can be increased proportional to the future energy costs savings. A second source of value uplift relates to the reduced exposure to stranding risk. By confronting a property's current energy standards with the pathway of future energy regulations, we can calculate an exact intersection moment in time, at which stranding risks become apparent. From that moment onwards, a retrofit can be undertaken to reduce this risk exposure. Not undertaking the retrofit would induce a series of increasing value discounts from that moment onwards, as a result of potential government penalties or as consequence of market obsolesce. A retrofit will shield the property from these negative value effects and discounts and will therefore result in a net value gain. Finally, the third source of value effects that we identified is a cluster of so-called indirect benefits that benefit the occupiers of the retrofitted property, including for example, improved employee satisfaction through reputational gains for both the property owners and tenants. These benefits will weaken over time, as enhanced building standards will drive change culminating in the gradual transition to "new" market averages.

In practice, measuring the size of these value effects is far from straightforward. Although the capitalisation of future energy cost savings ought to be simple, studies have shown that the calculations involved suffer from information limitations, perceived uncertainties regarding retrofit costs and future energy savings and bounded rationality of property owners, buyers and valuation professionals. From the literature, we learn that the capitalisation rate of the net energy costs savings is close to 70% (see Wallace et al, 2017). Regarding the positive value impact of the stranding risks shielding of retrofits, the literature offers evidence equalling 6.5% of transaction values, measured as brown discounts for the least energy efficient properties within the local commercial real estate markets (Kok and Jennen, 2012).Timely retrofits can help to prevent this type of future value discounts. Regarding the value uptake because of the cluster of indirect benefits, the available literature is inconclusive. However, studies for the US office markets of retrofitted properties identified a summed total premium of 10–20% value premia, compared to non-retrofitted properties (Geltner et al., 2017).

Our paper seeks answers to various important questions:

Q1. How do energy efficiency gains affect the value and valuation of properties?
Q2. To what extent will future policy measures affect current property prices?
Q3. How does a deep retrofit with energy efficiency improvement add value to a property?
Q4. What is the magnitude of these value effects?

In the remainder of this paper, we seek for appropriate answers. We first offer an overview of the body of knowledge on both green premia and brown discounts. We then incorporate these insights into a conceptual framework with which we can time carbon-reducing retrofit actions, we assess their value effects for the property and we offer the outcomes of an empirical analysis to shed some light on the magnitude of these value effects. We finalise our paper with a summary of our most important conclusions, their implications and an agenda for future research.

2.3 A Review of Green Premia

This section reviews the empirical evidence on the economics of energy efficiency retrofits in the context of pricing of buildings with high environmental performance. While there is no complete consensus on the capitalisation of energy efficiency, the majority of studies point to a “green premium”. Investment in energy efficiency is considered to provide multiple benefits to investors. Whether by directly reducing energy demand and associated costs or facilitating other co-benefits, the enormous potential of energy efficiency is highlighted. Other financial benefits of energy efficiency investments common for all countries are energy cost reduction, hedging against energy price volatility and extended building lifecycle (IEA, 2016).

Green buildings are often regarded as future-proof investments and as one of the most important areas for promoting a low-carbon economy. The precise definition of what constitutes a “green building” is debatable. In the EU, the Energy Performance Certificate (EPC) of the building is the most common measure used to assess how “green” a building is. The EPC is expressed on a letter scale, from A to G, where A is the most efficient and G is the least efficient. EPCs must also highlight the most cost-effective measures that can be implemented in the property to reduce the carbon footprint. The primary objective of this green certification is to reduce uncertainty about quality and to drive prices by subsequently generating an increase in the demand for energy efficient buildings. For example, in the case of properties that have been subjected to green retrofit measures, the owner, through the price mechanism, can use the EPC certificate to signal the efficiency level of the property they are selling, enabling them to recoup their initial retrofit investment via higher capital gain if the value outweighs the cost. Buyers in the market, on other hand, can use the EPC rating and information to screen out inefficient properties by opting for favourable EPC rated dwellings which can be easily let out and command higher rent. The EPC can also be used to assess the likely retrofit investment the property may require to reduce energy consumptions and associated energy costs. Alternatively, prospective buyers of energy inefficient buildings will use poor EPC scores as a basis for negotiating down the price culminating in what the market conceive as a "brown discount".

2.3.1 Literature on the capitalisation of green features into sale prices

The past decade has witnessed a marked escalation in the volume of research examining the relationship between the energy and financial performance of real estate assets. Much of the research on the capitalisation effect of energy efficiency within European property markets has initially at least focused on the residential sector. Residential property has assumed a value effect of green retrofits increasingly prominent role within institutional portfolios in recent years, while improving the energy efficiency and carbon intensity of European housing stock has the greatest impact potential, in terms of attaining the decarbonisation goals depicted in the 2015 Paris Agreement – thus forming a logical starting point for this review. The rationale for improving energy efficiency as well as the capacity to adopt green retrofit solutions varies extensively across the residential sector premised on ownership profile and the nature of incentives or policy obligations. In the case of home owners, for example, motivations may center around reducing energy and associated running costs or if they are motivated to sell their property, for example, if energy retrofit adds value over and above the cost of the retrofit action, this serves to optimise the sale price. For investors, including institutional investors, the range of motivations while including value creation, other factors such as tenant satisfaction, tenant turnover, rental premium as well as the Environment, Social and Governance (ESG) credentials of the company all feed into the decision-making framework.

A study by Brounen and Kok (2011) examined the impact of energy labels on house prices in The Netherlands. Their research suggests that energy labels encourage transparency in the energy efficiency and that this information is capitalised into house prices. By studying the transaction processes of approximately 32,000 properties between 2008 and 2009, they found that residential properties with green labels rated A, B and C command premia of 10%, 5.5% and 2.2%, respectively, relative to properties rated D. The data set contained a large number of control variables and attempts were made to reduce the likelihood of biases in the sample by using the Heckman‘s correction for selection bias. In another closely related study, Hyland et al. (2013) applied a standard hedonic method to show that for a sample of 15,060 Irish dwellings on the market between 2008 and 2012, there was a 9.3% price premium for A-rated dwellings compared to D-rated dwellings. Fuerst et al. (2015) drew a similar conclusion by reporting a price effect of higher energy performance in the English housing market for a large sample of sale transactions. They report significant positive premia for dwellings rated A/B (5%) or C (1.8%), compared to an average D-rated dwelling. A small but positive relationship between energy performance and sale prices is also found for the housing market in Northern Ireland (Davis et al., 2015). Furthermore, a recent study of the Danish housing market suggests that energy performance ratings of properties play an important role in relation to sale prices (Jensenet al., 2016).

The studies above suggest a significant price premium attached to properties with favourable energy efficiency ratings. Other studies, however, suggest a weak or negligible impact on prices. By using Swedish housing transactions between 2009 and 2010, Cerin et al. (2014) show that energy performance is not rewarded across all property-price classes and ages of residential properties. They also show that there is little evidence of price penalties for the least energy efficient properties, although, within the most energy efficient houses, a statistically significant association between energy performance certification and house price is reported. In a related study, Amecke (2012) surveyed owner-occupied dwellings in Germany that were purchased after 2009, the year when the EPC became obligatory for domestic buildings in Germany. Through examining factors affecting purchasing decisions, they conclude that the impact of EPCs is insignificant and unhelpful in understanding the financial implications of the energy efficiency of a dwelling. These findings are mirrored in a more recent study of Fregonara et al. (2017) who used a hedonic model to examine the relationship between house price and EPC ranking in Turin.

Table 1 Empirical studies investigating the capitalisation of energy efficiency in Europe

Studies	Methods	Country	Results
Amecke (2012)	Standard Hedonic Model	Germany	Energy performance certificates have a limited effect on purchasing decisions
Brounen & Kok (2011)	Heckman‘s two-step estimation (FGLS)	Netherlands	Buildings with a green label sell at a premium of 3.6% relative to otherwise comparable houses with a non-green labels.
Cerin et al. (2014)	Standard Hedonic Model	Sweden	Energy rating does not on average contribute to the market price premium of a house.
Davis et al. (2015)	Standard Hedonic Model	Northern Ireland	A small but positive relationship between energy performance and sale prices.
Fuerst et al. (2015)	Standard Hedonic Model	England	14% premium of the highest band of energy ratings relative to lowest band.
Fuerst et al. (2016)	Standard Hedonic Model	Wales	18.5% and 4% for A/B rated and C rated buy-to-let properties and no significant discount for lower-rated properties.

Studies	Methods	Country	Results
Hyland et al. (2013)	Standard Hedonic Model	Ireland	A-rated properties receive a price premium of 11%, B-rated properties of 5.8% relative to D-rated properties.
Högberg (2013)	Standard Hedonic Model	Sweden	Home buyers take into account the information available in the EPCs which entail a price premium.
Jensen et al. (2016)	Standard Hedonic Model	Denmark	Energy performance ratings of properties play an important role in relation to sales prices.

Table 1 presents a summary of these empirical studies examining the possible impact of energy efficiency ratings on European house prices. The evidence for a price premium is partly contradictory, but it is generally skewed to a premium in terms of higher transacted prices for properties with high environmental performance. Despite this, it is quite apparent that there is a clear lack of empirical studies examining the effect of green certificates on rents in either the residential of commercial property markets.

2.3.2 Literature on the capitalisation of green features into rental prices

Empirical research examining the capitalisation of energy efficiency on rental returns is extremely limited. The apparent gap in the literature is not surprising, given the inherent shortage of high quality data. To a greater extent, previous analyses of this topic have examined the effect of energy efficiency ratings in the commercial office market. This more established literature has typically relied on appraisal-based data or asking rent data to show a significant and positive link between energy efficiency ratings and office rents. For instance, an early study by Banfi et al. (2008) suggests that tenants are prepared to pay up to 13% higher rent for buildings that have adopted energy-saving measures. Similarly, Eichholtz et al. (2013) report that office buildings that were labelled energy efficient by one of the two major US rating agencies (Green Building Council and EPA's Energy Star) command a "green" rental premium relative to office buildings that were never certified. They estimate that, holding property characteristics constant, an office building registered with LEED or Energy Star commands an average green rental premium of 3%. This green premium is found to be higher for buildings with a triple net rental contract, suggesting that tenants prefer to pay energy bills separately when leasing space in green office spaces.

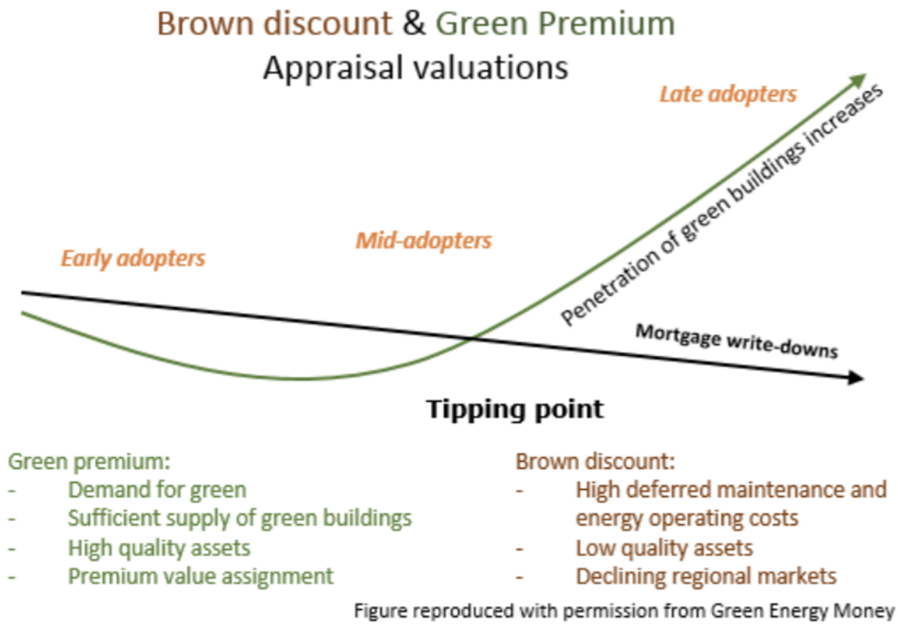
In a related study, Fuerst et al. (2013) use a data set containing actual contract rents and lease terms to show that UK office spaces with favourable energy performance ratings attract a significant rental premium relative to buildings with average energy performance ratings, although this premium is largely limited to highly energy efficient newly built buildings. Investors in the residential rental market are likely to be different from investors in commercial buildings in the absence of easily accessible information on the energy efficiency of buildings (Kok and Kahn, 2014).

Despite an infusion of institutional capital into the residential sector in Europe over the course of the past decade, empirical literature emerging from the private rental market has up until now been very limited. Data quality concerns are often cited as limitations and there is no clear consensus on the scale of the price effect of energy efficiency yet. A few case studies from Sweden, Germany and Ireland report a positive relationship between energy efficiency ratings and residential rents. Zalejska-Jonsson (2014) uses a Swedish database that includes occupants living in green and conventional multi-family buildings to show a green premium of 5% of total rent. However, environmental certificates are found to have a negligible effect on renting decisions. Similarly, Hyland et al. (2013) adopt a Heckman's selection technique to investigate the effect of energy efficiency ratings on Irish residential property values and rents. They report that relative to D-rated properties, A-rated properties have a green sale price premium of 11% and a green rent premium of 1.9%. Interestingly, not only does this study suggest a positive relationship between energy efficiency ratings and rental and sale prices, but it also suggests that buyers exhibit a stronger willingness to pay for energy efficiency than tenants. In related research, Kholodilin and Michelsen (2014) examined the residential rental market in Berlin and found that energy efficiency savings are generally capitalised into rental prices. Earlier, Rehdanz (2007) arrived at similar conclusions in a study of German housing markets. Some evidence therefore exists that green buildings do command higher rental prices than conventional ones.

2.4 The Case and Causes of Brown Discounts

Appraisers will be able to produce more realistic market valuations if they consider green features of the property, such as energy efficiency or indoor air quality. Moreover, existing conventional buildings will become obsolete and experience the so-called "brown discount" if they do not adapt to the increasing demands of tenants and regulators regarding sustainability features. Because of increasing stringency of regulatory requirements, these latter buildings and properties fall below standards and become less attractive because of increasing level of necessary economic input for upgrading. A framework that illustrates the market forces and dynamics underlying brown discount was introduced by the Green Energy Money blog (2016) (Figure 1). Figure 1 illustrates how the gradual uptake of green building premia eventually intersects with downwards sloping valuation of write-offs, creating a tipping point from which onwards brown discounts are associated with properties that fail to meet sustainability standards. The concept of "green value" or "green premium" was introduced in 2005 by the Royal Institution of Chartered Surveyors (RICS) and was used more widely in the real estate business from 2010 (Hartenberger et al., 2017). While in the USA, "Green Value" is used to refer to a variety of sustainability and environmental properties (including water and waste efficiency and resilience to flooding, even for social aspects); in Europe, the term refers mostly to energy efficiency and low carbon features. It has been long and often discussed whether more sustainable buildings are valued somewhat higher as a direct result of their better performance.

Figure 1: The future trend of green buildings taking over the market because of non-sustainable buildings going obsolete



Source: Green Energy Money (2016)

But there is also empirical evidence for the opposite effect of brown discounts. For instance, Kok and Jennen (2012) published results that measured brown discounts for a large sample of 1,100 leasing transactions within the Dutch office market during the period 2005–2010. They show that buildings that have been certified and designated as inefficient (with an EU EPC of D or worse) command rental levels that are some 6.5% lower as compared to energy efficient, but otherwise similar buildings (labelled A, B and C). Moreover, new policy measures prohibiting leasing out commercial properties that fail to meet minimum energy efficiency standards have been announced in The Netherlands and in the UK.[1] Obviously, the outlook of rental vacancies because of these regulations will depress property values in the future and cause brown discounts. These recorded green premia and brown discounts can help to assess the spread that appraisers need to incorporate into their future valuation based on the energy efficiency standard of the property at hand.

Besides these value and valuation effects, energy efficiency can also impact properties market liquidity. Becoming a stranded asset will first materialise into slower update numbers and a longer time on the market (TOM) during sale processes. Tenants and potential buyers will consider the relative energy efficiency level of the property and before this will materialise into the transaction price effects, the first effect may well be that buyers and tenants shy away from the offered property as they prefer more efficient alternatives. In that case, the liquidity or illiquidity of inefficient properties

[1]Since April 1st 2018, landlords of non-domestic private rented properties (including public sector landlords) may not grant a tenancy to new or existing tenants if their property has an EPC rating of band F or G (shown on a valid EPC for the property). This applies to existing tenancy agreements from 2023.

will precede the price effects. Liquidity is an important consideration for owners and investor of real estate, besides price stability, as real estate is already categorised as a less liquid asset category. Ending up with less than average liquidity will create risks that investors and buyers want to know *ex ante*.

Within the European real estate market, EPCs have been introduced as carriers of relevant information. They can inform tenants and buyers about the relative size of their future utility bills. Bills that can widely range depending on the energy efficiency standard of the property. Still, until recently, this thermal quality element has long been absent in the sale process between sellers and real estate buyers. Buyers did not ask, and sellers did not tell. In line with Akerlof (1970), we expect that EPCs can serve as a means for reducing this informational asymmetry between sellers and buyers, which is one of the aims of energy policy (see Gayer and Viscusi, 2013; Mannix and Dudley, 2015). Houde (2014) already demonstrated that energy certification can act as a reliable substitute for more accurate, but complex, energy information. But that said, EPC information will not bridge the full information asymmetry.

The success of a real estate transaction depends on the price and speed of sale. Typically, sellers strive for a quick sale at the highest possible transaction price. While prices can be boosted by not disclosing all negative attributes. Taylor (1999) showed that buyers shy away from homes for which qualities are not known. Buyers prefer to bid on homes with full(er) information even if the information is not necessarily positive, as they want to be protected from having to undertake time and resource consuming activities that may yield that information. This adaptation from Akerlof's Lemon's problem within the real estate market predicts that the speed of sale increases with information. In Aydin et al. (2019), a first empirical analysis of these liquidity effects is performed on EPCs' value as carriers of information by testing their effects on the TOM of housing transactions. The authors study the Dutch housing market, as The Netherlands was one of the first countries to adopt EPCs in the housing market on a national scale in 2008. This early adoption creates a rich data setting, as Dutch EPCs have been around for close to 12 years. Their results indicate that EPC information effectively enhances the speed of sale, as TOM decrease when dwellings are labelled. These TOM reductions vary between 7% and 22%, depending on model specifications and estimation approaches. In all cases, the effect is significant and increases as labels are provided earlier during the sale process and convey positive ratings. Apparently, good news travel faster and shorten the sale journey.

From a policy perspective, the quality of data remains a key barrier to the upscaling and expansion of green retrofit solutions. Nonetheless, recent research by Marmolejo-Duarte and Chen (2019) is highly insightful in that it serves to not only showcase the impacts of EPC rating on property price but perhaps more pertinently highlights a capacity gap when it comes to retrofit intervention. Their research on the Barcelona housing market infers that EPC ratings have "modest" impacts on listing prices. Their research highlights that for the cheapest apartments and apartments located in low-income areas, the "brown discount" derived from poor EPC ratings is enormously significant, potentially depreciating the equity of those who have the least resources to carry out an energy retrofit.

The retrofit “capacity” gap presents challenges for all major cities in terms of policy formation and the range of incentives needed to decarbonise the built environment. Moreover, many of the most carbon intensive assets reside within public sector asset portfolios. Constraints on capital budgets ensure that the challenge of retrofit applies not only to low-income home owners but also many cash strapped municipalities. As such the business case and credibility of the evidence base to support green retrofit intervention is critically important.

Historically, simple payback models were used to support the business case. The payback model in essence measured the capital costs of the retrofit intervention relative to the energy cost saving accrued over time following the intervention (Kelsey and Pearson, 2011). The payback model has nonetheless been criticised for failing to take account of the long-term benefits beyond the initial capital recovery while early versions of the payback model assumed energy prices to remain constant (Jones and Bogus, 2009).

The payback model was to some extent displaced following the introduction of life cycle cost analysis (LCCA). The LCCA method aims to determine whether a retrofit investment will generate a positive return on investment over the life of the retrofit technology. LCCA uses internal rate of return and net present values as specific measures to inform the nature and extent of the retrofit decision. LCCA is a much more comprehensive approach than the payback method in that it considers interest, inflation, utility price increases and annual energy savings. However, LCCA neglects an important factor which might not be immediately tangible in a financial sense, but which actually comprises the largest expense of any commercial building, i.e. the tenants (Carlson and Pressnail, 2018).

The latest development in building energy retrofit economics is the idea that an energy retrofit will affect building asset value. Section 2.5 will duly explore the latest thinking around the dominant sources of value creation and the extent to which this can ultimately be captured from a valuation viewpoint and capitalised from an owner/investor perspective.

2.5 Three Sources of Retrofit Value

A lack of relevant information, or difficulties of processing information, can inhibit owners and investors willingness to invest in energy efficient retrofits, as future gains are uncertain.This is certainly true for any value effects of green retrofits, as these can only be verified *ex post.* The value capture element of green retrofit is important *ex ante*, as this future indirect benefit is often missing in the payback period calculations that are frequently used when analysing energy efficiency investments.

Recently, a consortium of European research institutes cooperated to compile the Carbon Risk Real Estate Monitor (CRREM). The CRREM framework enables property owners to quantify and include the intended retrofit investments, and besides calculating the net carbon impact (plus energy cost savings and stranding risk reduction) the CRREM framework offers an estimation of the capitalisation rate of this investment on the property value as a result of the retrofit. This framework identifies and specifies three specific sources of retrofit value effects:

A: The capitalisation rate of energy savings.

B: The increasing exposure to the value discount due to stricter standards.

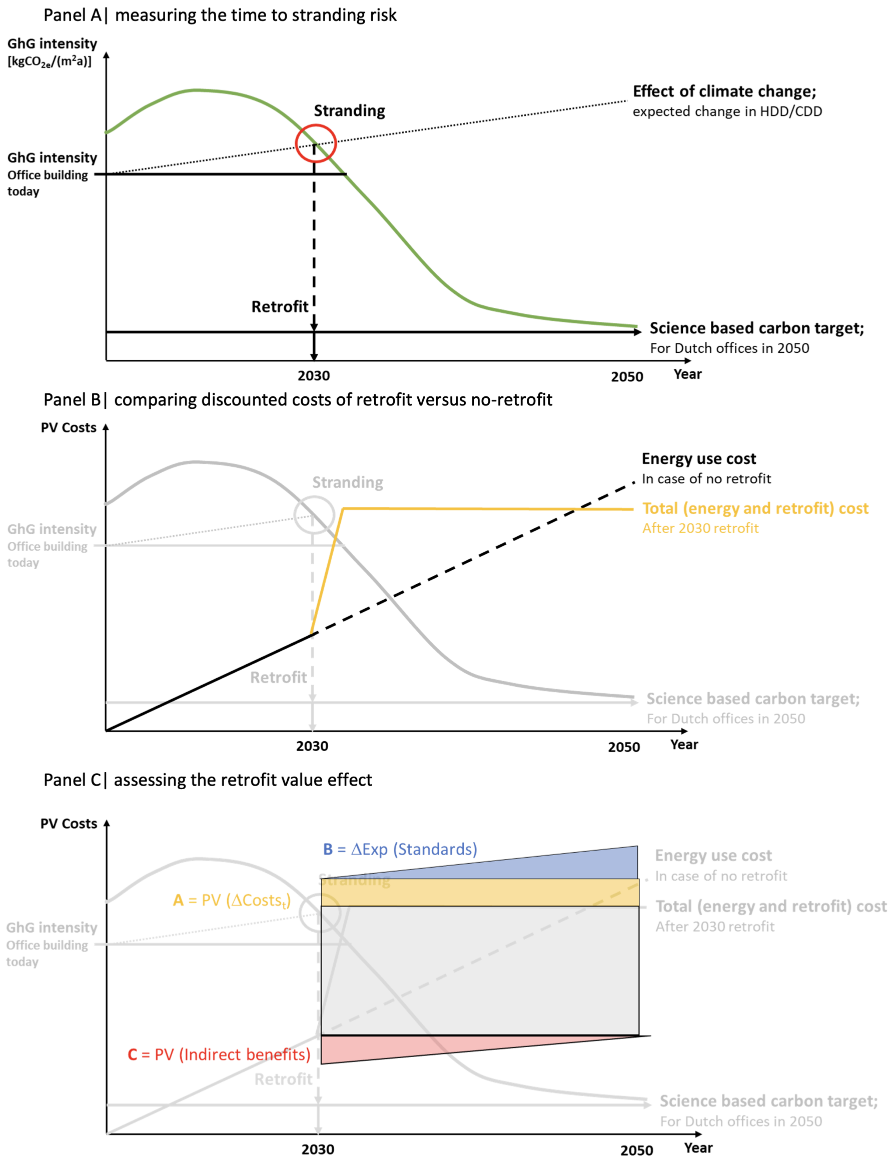
C: The value uplift due to indirect benefits (health, employee satisfaction, marketing, etc.).

The combined sum-effect of these three will benefit the property owner after the retrofit and therefore ought to be acknowledged during the *ex ante* retrofit analysis. To illustrate the framework, we like to use the example of an owner and landlord of a Dutch office building. The building was constructed in 2005 according to the building codes at the time. This means that the GHG intensity of the property – the kg $CO_2e/(m^2a)$ – is determined during construction and is assumed to be constant over the lifetime of the property. Let us assume that today's appraised market value of this fully leased property is €10 million and that the discounted value of the expected energy costs for the remaining lease period equals €1 million and is known by both the owners and the tenants, who are all assumed to be fully informed and rational. Property owners will be familiar with the Paris Agreement, but unaware of how this will affect demand for their property. Hence, many property owners decide to wait until measures are taken or they are forced to take action.

The CRREM framework offers property owners and investors an alternative to this passive "wait and see" strategy. Instead, the framework offers three pathways, presented in Figure 2. In panel A, investors are offered – in green – the most likely trajectory of the policy measures relevant for their office building. This curved line is based on the science-based targets regarding the GHG intensity of Dutch office buildings until 2050. Based on this pathway, the most reliable "time before stranding risk" is calculated as a function of this policy pathway and the current GHG intensity of the property. Please note that instead of using the horizontal curve, which ignores the projected effects of climate change and evolution of the decarbonisation of the grid on the energy use and GHG emissions of the property, the upward sloping curve that combines all is selected. The crossing point between this curve and the policy pathway marks the moment at which the property starts failing to align with future energy regulations. This crossing point marks the moment which introduces stranding asset risk as a result of energy policy misalignment. In panel A of Figure 2, we calculate that the subject property has 10 years until 2030 before this crossing point is reached. This is the first relevant output, as stranding risk will eventually deteriorate the property value, and the CRREM framework helps real estate investors to assess the period during which you can proactively ensure that their property is repositioned to reduce this avoidable risk. This prediction will also enable investors to coordinate the required retrofit actions with their tenancy schedule and planned preventive maintenance, minimising void periods, tenant disruption and expenses.

Panel B of Figure 2 illustrates how this active repositioning can be examined financially. Please note that from this diagram onwards, the y-axis displays the present value of costs. Against the background of the panel A, insight regarding the timing

Figure 2: Stylized example to illustrate CRREM insights into stranding risk and retrofit decision



Notes: (a) Measuring the time to stranding risk; (b) comparing discounted costs of retrofit versus no-retrofit; (c) assesing the retrofit value effect of stranding asset risk now shows the financial payoffs of the alternative strategy of retrofitting the property in 2030 and thereby ensuring that the property aligns with the 2050 GHG regulations versus the status quo strategy in which the property is not retrofitted at all.

From this information, an investor would then move to panel C in which the value impact of this retrofit is estimated in three components. Knowing that the present value of the energy use (status quo) equals €1 million, and knowing that the required retrofit will take one year to execute, incurs €800,000 in present value terms and will result in no energy costs for the tenants afterwards, enable investors to assess the value potential of this retrofit action on the property value. Assuming rational decision-making, investors should expect that the €800,000 retrofit costs would be fully offset with the proportional gain in rents that the landlord is able to charge and that the tenants are willing to pay. In fact, €200,000 is left as a value premium because of the difference in discounted costs. In panel C of Figure 2, this premium is indicated as yellow area "A". From academic literature, we learned that in practice, these cost savings are not fully capitalised into market values. Empirical studies show that about 70% of projected (energy) cost savings are included in subsequent transaction prices. In this example, this would reduce the A-premium to €140,000, equalling 1.4% of the estimated market value of the property. This A-premium comes on top of an 8% value increase that is directly because of the retrofit investment, which is payed back by the outlook of zero energy costs and associating rent increases. The retrofit also shields the property for the effects of stricter standards and GHG regulation. In the case of the status quo strategy, this would have introduced stranded asset risk and would invoke increasing value discounts to the future property valuations. This is indicated in blue as area B in panel C of Figure 2. The size of this discount (here displayed as additional costs) has been documented in the literature as brown discounts that can accumulate to 6.5% of the transaction value. In this case, however, this B-component will be modest at first, because stranding risk kicks in after 2030 and will increase with the downwards slope of the green policy pathway curve. As years go by, the discrepancy between the GHG-intensity of the not-retrofitted property and new regulations will build up and increase the value discount that marks this discrepancy. Finally, it is reasonable to assume that investors can also expect value uplift after the retrofit, which is not just a function of direct cost savings. This C-component in panel C of Figure 2 includes the indirect benefits of, for instance, enhanced employee health and improved marketing and promotion potential that reduced carbon footprint actions can yield. A recent survey evidence by the USGBC (2018) affords a wider overview of employee benefits related to green buildings. Nonetheless, these benefits are difficult to measure, and empirical proof on this is scarce and weak. It is also known that this C-premium will also reduce over time, as the competitive advantage of the retrofit improvements will erode as years pass.

2.6 Empirical Analysis

To assess the magnitude of the value effects of energy retrofits in line with the conceptual framework of Section 2.5, we performed a small empirical analysis. For this analysis, we make good use of data provided by Immobilienscout24, the leading real estate platform in Germany. The total data set comprises about 24,000 listings for residential properties (apartments as well as detached-, semi-detached houses, etc.) for the city of Munich in the time period 2012–2015. As the information is entered by platform users, the data is subject to data entry bias. We therefore cleared the data of implausible values such as zero or negative area and of missing values that are required for the estimation such as energy consumption. After optimisation, 8,956 cross-sectional observations remained.

Table 2 Summary statistics

Variable	**Mean**	**Median**	**Std.Dev**	**Min.**	**Max.**	**N**
Price	505,696.92	438,250.00	326,286.25	67,000.00	2,840,000.00	8,956
Area	88.17	81.97	37.07	21.48	334	8,956
Price/m^2	5,515.54	5,295.21	1,743.82	951.46	17,192.17	8,956
Energy/m^{2}a	97.09	89.35	54.52	8.1	342	8,956
Floor	2.06	2	2.02	-1	23	8,956
Year constructed	1995.36	2000	19.54	1855	2018	8,956
Number of rooms	2.94	3	1.05	1	9	8,956
Number of bathrooms	1.28	1	0.48	1	7	8,956
Number of bedrooms	1.89	2	0.88	1	6	8,956
Price for parking	19,211.19	19,000.00	8,052.10	0	150,000.00	8,956
Year of last retrofit	2010.4	2012	4.68	1978	2016	2,339

Distribution of Categorical Variables

	Simple	Normal	Sophisticated	Luxury		
Quality of Equipment	0.01	0.19	0.51	0.1		8,956
	Yes (%)	No (%)				
Elevator	69	31				8,956
Balcony	91	9				8,956
Guest WC	40	60				8,956
Garden	33	67				8,956
Cellar	82	18				8,956
Built in kitchen	52	48				8,956
Retrofit from 2014	22	78				2,339

Table 2 presents the most important summary statistics of our data set and shows that 2,339 of the 8,956 units have been modernised. Almost 22% of those were retrofitted in the years from 2014, which is depicted by the distribution of the dichotomous variable "Retrofit from 2014". In 2014, the last major amendment to Energieeinsparverordnung (EnEV; German Energy Saving Ordinance) came into force. EnEV represents an important instrument of German energy and climate protection policy as the EnEV is intended to help ensure that the German Government's energy policy goals, in particular, a virtually climate neutral building stock will be achieved by 2050. Among other things, the EnEV issued an order that in advertisements of buildings that have an EPC, the energy efficiency class of the building must be indicated. The energy efficiency class is based on the total energy consumption per square meter of living space per year (kWh/m^{2}a). Accordingly, and similar to Cajias, Fuerst & Bienert (2019), we are using energy consumption classes as a second proxy besides absolute energy consumption by assigning each observation to the respective consumption class. Consumptions defined in EnEV in (kWh/m^{2}a) were used as thresholds. Table 3 depicts the distribution of energy classes in the data set and reports correlation coefficients for both of the energy proxies and price per square meter.

Table 3 Correlation matrix

Variable	Mean	Price/m^2	Energy/m^{2}a	A+	A	B	C	D	E	F	G
Price/m^2	5515.54	1									
Energy/m^{2}a	97.09	-0.4	1								
A+	0.10	0.13	-0.48	1							
A	0.14	0.27	-0.40	-0.13	1						
B	0.18	0.22	-0.31	-0.16	-0.19	1					
C	0.13	-0.03	-0.07	-0.13	-0.15	-0.18	1				
D	0.15	-0.20	0.14	-0.14	-0.17	-0.20	-0.16	1			
E	0.15	-0.21	0.37	-0.14	-0.17	-0.20	-0.16	-0.18	1		
F	0.11	-0.15	0.50	-0.12	-0.14	-0.17	-0.13	-0.15	-0.15	1	
G	0.03	-0.07	0.41	-0.06	-0.07	-0.09	-0.07	-0.08	-0.08	-0.06	1
H	0.01	-0.03	0.21	-0.02	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02	-0.01

Our econometric approach to examine whether higher energy consumption comes along with a significant price penalty or a reduced consumption with a premium involves two steps. Firstly, we estimate a standard hedonic pricing model as empirically justified by Sirmans et al. (2005). By that we use price per square foot as response variable and absolute energy consumption as energy proxy. In a second step we use partial residual plots to identify possible nonlinear relationships between predictor and response variables (Brunauer et al., 2010). By visual inspection, it is found that five covariates suggest nonlinear modeling, namely, area, number of bathrooms, floor, price for parking and energy consumption. Consequently, these are modeled non-linear within an additive mixed approach with mixed covariates of parametric estimates and nonlinear functions. The baseline price model looks as follows:

$$Y = X\beta + f\left(x_i\right) \tag{2.1}$$

With building factors (i), binary spatial variables for geographic regions [S] based on ZIP code level (j), energy consumption [EC] proxies (k) and age [K] controls (t):

$$log(price/m^2)_i = \ \beta X_i + \ \theta S_j + \ \mu \mathrm{EC}_k + \ \lambda K_t + \ \varepsilon_i \tag{2.2}$$

X holds both linear and non-linear characteristics. We estimated six different model specifications of which three are solely linear. Three more with mixed linear and nonlinear covariates whereas non-linearity is accounted for by modeling the nonlinear covariates with penalised splines. As can be seen from the correlation matrix above, the turning point of the sign of the correlation coefficient for the energy classes and price is between class C and B. We therefore choose to eliminate class C from the vector *EC* for model estimation and by that setting class C as the reference category. This brings the expectation with it that higher classes from A+ to B will show a positive sign and by that a green premium, while lower classes will show a negative sign and by that a brown discounts.

Table 4 Regression model output

log(price/m^2)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Method	OLS	OLS	OLS	GAM	GAM	GAM
Constant	8.523***	8.448***	8.418***	8.668***	8.646***	8.609***
	(0.029)	(0.023)	(0.024)	(0.017)	(0.018)	(0,019)
log(energy/m^2 a)	-0.010**			4.506***		
	(0.005)			(edf)		
A+		0.048***	0.046***		0.044***	0.041***
		(0.011)	(0.011)		(0.010)	(0.010)
A		0.076***	0.074***		0.071***	0.069***
		(0.010)	(0.010)		(0.009)	(0.009)
B		0.025***	0.024**		0.025***	0.024***
		(0.009)	(0.009)		(0.008)	(0.008)
D		-0.016*	-0.015*		-0.015**	-0.014**
		(0.008)	(0.008)		(0.007)	(0.007)
E		0.004	0.0003		0.007	0.005
		(0.009)	(0.009)		(0.008)	(0.008)
F		0.023**	0.020**		0.019*	0.016
		(0.009)	(0.009)		(0.009)	(0.009)
G		0.01	0.09		0.003	0.002
		(0.014)	(0.014)		(0.013)	(0.013)
H		0.053	0.050		0.053	0.050
		(0.032)	(0.032)		(0.030)	(0.030)
Retrofit from 2014			0.032***			0.030***
			(0.006)			(0.005)
Linear Covariates	15	15	15	11	11	11
Non-linear Covariates	0	0	0	4	4	4
Age Dummies	8	8	8	8	8	8
Spatial Dummies	75	75	75	75	75	75
N	8,928	8,928	8,928	8,928	8,928	8,928
Adjusted R^2	0.610	0.614	0.615	0.677	0.677	0.678
AIC	-4125	-4196	-4225	-5768	-5774	-5805

*Notes: Significant at *10, **5 and ***1% levels; standard errors in brackets below the estimated coefficient. edfs are reported for nonlinear estimates within nonlinear models. The estimated coefficients are marked with “edf” in brackets below. The reported significance shows the significance of smooth terms.*

Table 4 holds the estimation results for models (1)–(6) and shows the results for both the linear ordinary least squares (OLS) and mixed-linear GAM estimations.[2] In both cases, we present our model results in three versions. In the first two models, we estimate the appreciation and capitalisation of energy efficiency. For our OLS model, we find that enhanced energy efficiency (either lower energy intensity or better energy labels) is associated with higher property prices. For both model estimates, we find that the gain from an average C-label to an A-label lifts property prices with 7.1 to 7.6% – depending on model specifications. This serves as an empirical proxy for the size of the A and B areas of Figure 2. When we also control for the retrofitting in our sample, we find that A- over C-label bonus drops to 6.9 to 7.4%, while the residual value effects (C area of Figure 2) of the retrofit are priced at a premium of 3.0 to 3.2%. In other words, our Munich analysis shows that the sum effects of retrofits that improve C-label dwellings to an A-label standard add 10% value in total. A value effect, that is partly because of the validated energy efficiency gains, while offering another 3% for non-energy efficiency related improvements.

2.7 Conclusions and Implications

In this paper, we focused on the value effects of green retrofits of real estate. The rich literature on green premia was reviewed to proxy the size of the value effects of energy efficiency improvements. The existing knowledge base identified various sources of value capture mechanisms that can be related to retrofit actions.

We introduced a conceptual framework – the CRREM framework – which helps to identify and measure three types of real estate value effects that can result from a green retrofit. Given that these retrofits are undertaken and calibrated to reduce energy use (and costs), a first source of value effects should be the capitalisation of future energy cost savings. As long as the net present value of future energy costs savings exceeds the immediate retrofit investment, we expect a proportional "green" premium of the property right after the retrofit is finalised. In case of owner-occupiers, the outlook of lower energy costs will directly be included in the budget of the users' lifecycle costs. In case the property is leased, the same value effect should appear as long as rents can be increased proportional to the future energy costs savings. A second source of value effects relate to the reduced exposure to stranding risks. The CRREM framework identifies the moment at which the property's current energy standards will intersect with a pathway of future energy regulations and standards. At that intersection, stranding risks becomes apparent, and a retrofit can be undertaken to reduce this risk exposure. Not undertaking the retrofit would induce a series of increasing value discounts from that moment onwards, as a result of potential government penalties or as consequence of market obsolesce. A retrofit will shield the property from these negative value effects and

[2] We also include a more elaborate output table than Table 4, including all covariates, in the Appendix of this chapter. This table includes the same coefficients on the most relevant matters (energy efficiency and retrofitting), while also showing coefficients for the appropriate controls (area, floor, parking etc.) which are all in line with both intuition and the literature.

discounts and will therefore result in a net value gain. Finally, the third source of value effects that we have identified is a cluster of so-called indirect benefits that vary from enhanced employee satisfaction to reputational gains for the property users involved. These benefits will wear down over time, as the enhanced building standards will gradually fall back to market averages.

In practice, measuring the size of these value effects is far from straightforward. Although the capitalisation of future energy cost savings ought to be simple, studies have shown that the calculations involved suffer from information limitations, perceived uncertainties regarding retrofit costs and future energy savings, and from bounded rationality of property owners, buyers and valuators. From the literature, we learn that the capitalisation rate of the net energy costs savings is close to 70%. Regarding the positive value impact of the stranding risks shielding of retrofits, the literature offers evidence equalling 6.5% of transaction values, measured as brown discounts for the least energy efficient properties within the local commercial real estate markets. Timely retrofits can help to prevent this type and size of future value discounts. Regarding the value uptake, because of the cluster of indirect benefits, the available literature is still inconclusive. However, studies for the US office markets of energetic retrofitted properties identified a summed total premium of 10% to 20% value premia, compared to non-retrofitted properties.

Apart from the relevant insight into these value effects that have been documented in the available literature, we also offer our own empirical evidence. After analysing data from the Munich real estate market, we find an aggregate retrofit premium of around 10%. A premium which can largely be attributed to the gains in energy efficiency from a standard C label to a more future proof A-label, while offering around 3% value uplift for the indirect benefits.

The insights that are offered in this paper can help real estate owners and investors during their *ex ante* analysis of future energetic retrofit investments. Instrumentalising the various value effects that have been identified in this paper is not straightforward. At the same time, ignoring these value effects would delay or abort retrofit actions. As soon as an outlook on consistent government actions becomes available, real estate valuers will be able to absorb the effects of future sanctions in today's appraisals of the properties. Finally, regarding the wide range of indirect benefits that range from marketing benefits to improved employee's health, more empirical research is needed to allow for an estimation of future value effects.

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2.9 Appendix

Table 5 Regression model output for all variables

log(price/m^2)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Method	OLS	OLS	OLS	GAM	GAM	GAM
	(0.029)	(0.023)	(0.024)	(0.017)	(0.018)	(0.019)
log(energy/m^{2}a)	-0.010**			4.506***		
	(0.005)			(edf)		
A+		0.048***	0.046***		0.044***	0.041***
		(0.011)	(0.011)		(0.010)	(0.010)
A		0.076***	0.074***		0.071***	0.069***
		(0.010)	(0.010)		(0.009)	(0.009)
B		0.025***	0.024**		0.025***	0.024***
		(0.009)	(0.009)		(0.008)	(0.008)
D		-0.016*	-0.015*		-0.015**	-0.014**
		(0.008)	(0.008)		(0.007)	(0.007)
E		0.004	0.0003		0.007	0.005
		(0.009)	(0.009)		(0.008)	(0.008)
F		0.023**	0.020**		0.019*	0.016
		(0.009)	(0.009)		(0.009)	(0.009)
G		0.01	0.09		0.003	0.002
		(0.014)	(0.014)		(0.013)	(0.013)
H		0.053	0.050		0.053	0.050
		(0.032)	(0.032)		(0.030)	(0.030)
Retrofit from 2014			0.032***			0.030***
			(0.006)			(0.005)
Area	0.001***	0.00***1	0.001***	7.869***	7.906***	7.906***
	(0.0001)	(0.0001)	(0.0001)	(edf)	(edf)	(edf)
Floor	0.006***	0.005***	0.005***	4.013***	3.781***	3.783***
	(0.001)	(0.001)	(0.001)	(edf)	(edf)	(edf)
log(price for parking)	0.014***	0.015***	0.014***	8.923***	8.932***	8.935***
	(0.002)	(0.002)	(0.002)	(edf)	(edf)	(edf)
Number of bathrooms	0.030***	0.028***	0.027***	1.744***	1.693***	1.712***
	(0.006)	(0.006)	(0.006)	(edf)	(edf)	(edf)
Number of rooms	-0.017***	-0.015***	-0.015***	-0.007	-0.007	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Number of bedrooms	-0.019***	-0.021***	-0.021***	-0.022***	-0.023***	-0.023***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Elevator	-0.0002	0.003	0.004	-0.011**	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Guest WC	0.036***	0.036***	0.036***	0.029***	0.028***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Luxury	0.141***	0.142***	0.149***	0.103***	0.104***	0.111***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Sophisticated	0.057***	0.054***	0.060***	0.035***	0.034***	0.040***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

log(price/m^2)	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	GAM	GAM	GAM
Normal	-0.067***	-0.066***	-0.062***	-0.060***	-0.060***	-0.056***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Balcony	0.001	-0.004	-0.005	0.007	0.005	0.004
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Cellar	-0.024***	-0.022***	-0.021***	-0.011*	-0.011*	-0.010
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Garden	-0.008	-0.010**	-0.009*	-0.004	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Fitted kitchen	0.004	0.008	0.009*	0.005	0.005	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Linear Covariates	15	15	15	11	11	11
Non-linear Covariates	0	0	0	4	4	4
Age Dummies	8	8	8	8	8	8
Spatial Dummies	75	75	75	75	75	75
N	8,928	8,928	8,928	8,928	8,928	8,928
Adjusted R^2	0.610	0.614	0.615	0.677	0.677	0.678
AIC	-4125	-4196	-4225	-5768	-5774	-5805

*Notes: Significant at *10, **5 and ***1% levels; standard errors in brackets below the estimated coefficient. edfs are reported for nonlinear estimates within nonlinear models. The estimated coefficients are marked with "edf" in brackets below. The reported significance shows the significance of smooth terms.*

3. Multivariate Tail Risk Modeling for REITs: What Factors Drive Extreme Losses?

3.1 Abstract

The statistical modelling of daily REIT returns has been subject to a large number of conditional mean and conditional volatility models. However, these approaches estimate the conditional moments and corresponding risk metrics, based on the entire return distribution. Thus, the lower tail and extreme losses are not modelled explicitly. Subsequent univariate extreme value models marked a starting point for further improving tail risk modelling. Nonetheless, these univariate models do not fully capture the exogenous risk factors which affect the extreme losses of a public equity position. In order to extend univariate models, the present paper applies a novel multivariate extreme-value regression model explicitly for the lower tail of the return distribution below a chosen threshold. The study examines whether exogenous financial market covariates provide explanatory power for the estimation of Generalized Pareto Distributions in a non-linear generalized additive model framework. The main findings of this unique approach to REIT returns are that the explanatory power of covariates from equity and debt markets for the fit of Generalized Pareto Distributions is existent. However, the explanatory power differs across the analyzed impact factors and the model fit also varies across the eight tested REIT indices. From a more methodological perspective, shape parameters of the distributions are more sensitive to covariate inclusion than scale parameters, and the time effects of the models are both dynamic across time and clearly non-linear.

Keywords: REIT Returns, Extreme Value Regression, Generalized Additive Models, Tail Risk, Risk Management

3.2 Introduction

Extreme downturns of public equity markets have gained considerable interest in the past decade, due to experiences during the global financial crisis of 2008/2009 and the recent COVID-19 pandemic. Those extreme losses, which are located in the lower tail of the return distribution, denote observations with relatively low probability of occurrence, but severe negative financial impact on the value of the position. The statistical modeling of the specified portion of the return distribution has forced academia to develop procedures that are not based on the estimation of conditional moments of the entire distribution function (McNeil, 1997). Corresponding traditional conditional means, such as capital asset pricing models (CAPM) or generalized autoregressive conditional heteroscedasticity (GARCH)-based variance models of return time series, do not offer a suitable analytical framework for modeling the tails of financial return distributions (Bee, Dupuis & Trapin, 2019).

Accordingly, econometric literature in the field of finance shifted towards Extreme Value Theory (EVT) to describe the exceedances of the return distribution below a defined threshold, using Generalized Pareto Distributions (GPD) to model the extreme return observations (McNeil, Frey & Embrechts, 2005). In the financial literature, several studies have demonstrated the advantages of more flexible EVT-based return distribution tail modeling, in comparison to classic Gaussian approaches (Danielsson & de Vries, 1997), because public equity returns are known for excess kurtosis and so-called fat tails (dating back to Officer, 1972). This excess kurtosis is the central statistical moment for rejecting the assumption of normality for equity return distributions. In this context, REIT returns are a highly interesting field of study compared to classic equity positions such as the constituents of the S&P500, because the former show even heavier excess kurtosis than the latter (as recently studied by Fritz & Oertel, 2020).

Univariate EVT models which fit GPDs solely on the information from the time series itself have enabled capturing this feature of non-normally distributed tails of financial data (Longin & Solnik, 2001). In this context, McNeil and Frey (2000) introduced the return decomposition to an inner kernel density based on a normal distribution and outer GPDs above and below defined thresholds. Specifically for REITs, Liow (2008) showed the general favorability of univariate EVT models without exogenous covariates, through the improved fit of the tails and risk metric back tests for Value-atRisk (VaR) estimations. Nonetheless, the univariate EVT-based modeling of extreme REIT returns does not fully replicate the financial risk of public equity positions (Kiriliouk, Rootzén, Segers & Wadsworth, 2019), because their risk exposure can only be fully captured from additional exogenous risk factors. This exogeneity of financial risk is well documented for REITs in other modeling frameworks, with regard to the macroeconomic environment, as well as cross-dependencies towards equity or debt markets (Chan, Hendershott & Sanders, 1990; Stevenson, 2002; Chang, Cheng & Leung, 2011; among others). In order to deal with this aspect of exogenous tail risk factor modeling, Chavez-Demoulin, Embrechts and Hofert (2016) extended the econometric literature by a dynamic multivariate EVT regression model to allow for exogenous covariates to fit the tails of timely-variant time series data. This methodological advancement provides the analytical basis for addressing the abovementioned weaknesses of univariate EVT modeling and the time variance of REIT returns. To the best of the authors' knowledge, no study has so far modeled a dynamic multivariate EVT regression for REIT returns depending on exogenous covariates. The central benefit of these models is the enhanced understanding of the risk factors, which contain explanatory power for modeling the tails of REIT returns. Thus, the central research question of the present study can be summarized as follows: What exogenous risk factors yield explanatory power to describe the excesses located in the lower tail of REIT return distributions?

3.3 Literature Review on the Statistical Modeling of REIT Return Risk

In the financial literature, the return risk of public equity positions generally denotes the possibility of variability of intertemporal discrete value changes of the daily stock price p_t, expressed by $r_t = \log(p_t) - \log(p_{t-1})$ (e.g. Bachrach & Galai, 1979). From a methodological point of view, return risk is classically modeled by either linear multifactor CAPM, based on the seminal work of Sharpe (1964) and Lintner (1965) or GARCH models (Bollerslev, 1986). It is important to note, that this brief review replicates only the most prominent models for moments of the financial return risk with regard to conditional means (μ_t) and variances (σ_t^2), and the decisive differences from the empirical approach of the present piece. In the first cluster of classic linear risk factor models on conditional means, expected returns ($E[r_t]$) are a function of exogenous covariates, which are interpreted as risk factors (θ), expressed by (Hansen & Lunde, 2005):

$$\mu_t = E(r_t) = f(r|\theta) \tag{3.1}$$

This general idea of linear risk factor models was translated into an economically significant parametric specification for stocks, estimating the parameters ψ in the function $f(r|\psi(\theta))$ by the three or five factor model of Fama and French (1993; 2015) for the expected value of excess returns $R_{i,t} - RF_{i,t}$ (see equation 3.2):[1]

$$R_{i,t} - RF_{i.t} = \alpha_i + \beta_i (R_{Mt} - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t} \tag{3.2}$$

In addition to the Fama-French risk factors of stock returns, the literature has focused on additional risk factors to capture further explanatories, thus reducing the error component e_{it} (for REITs, e.g. Chan, Hendershott & Sanders, 1990). The parameter estimates for any additional exogenous risk factors are generally known as factor loadings. In the existing body of literature, authors generally argue that statistical significance of factor loadings constitutes the empirical evidence of the proposed theoretical relationship between return risk and the covariates (recently for REITs, e.g. Carmichael & Coen, 2018). However, as noted above, the linear multifactor model provides evidence of the impact of risk factors on the conditional mean (μ_t) of the excess return, which equals the expected value ($\mu_t = E[R_{i,t} - RF_{i.t}]$). Accordingly, these models are unsuitable for the present study, which aims explicitly

[1] The risk factors of the Fama-French model are neither named nor explained here. See Fama & French (2015) for a thorough reproduction. The equation only represents the basic idea for stock return risk factor models.

at modeling the tail. The second group of prominent models is the family of GARCH models. Univariate GARCH models were originally introduced by Bollerslev (1986), aiming at modeling conditional variance:

$$\sigma_t^2 = var\left(r_t\right) = f(r|\theta) \tag{3.3}$$

Originally, the parametric approach of the univariate GARCH ($f(r|\psi\left(\theta\right))$ model let the variance to be conditional only on p past realizations of the time series variance (σ_{t-i}^2), as well as q past error terms (ε_{t-i}^2) as impact factors (θ), leading to the general notation of GARCH (p, q):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3.4}$$

GARCH models were also extended by the functional relationship or potential asymmetries between past information and the estimated variance, such as exponential (Nelson, 1991), asymmetric (Glosten, Jagannathan & Runkle, 1993) or threshold GARCH (Zakoian, 1994) among others.[2] In addition to the univariate GARCH models, several authors have introduced exogenous factors to affect the variance of stock returns in multivariate GARCH specifications. In these models, θ not only contains past variance and error terms of the time series itself, but also exogenous covariates to affect the conditional return volatility of equation 3.4 (e.g. Jirasakuldech, Campbell & Emekter, 2009).

Thus, conditional variance specifications entail similar limitations to the tail modeling like the first mentioned multifactor models. Even though the dispersion of the distribution is addressed, conditional variance models do not explicitly model the tails, and therefore, not the extreme losses in a financial time series. Consequently, conditional variance models are not an effective methodological tool for addressing the tail risk either. Based on these limitations, researchers developed univariate EVT models across the broader finance literature and extending into the real estate segment to address extreme tail risk (e.g. Liow, 2008), underlining the decisive advantage of EVT. The application of an EVT approach allows to unambiguously model the tail of the return time series data only. This tail risk modeling is typically achieved by decomposing the financial time series data into an inner normally distributed kernel density and outer GPD-distributed tails (as motivated by McNeil, Frey & Embrechts, 2005).

Historically, the main motivation to turn away from the normal distribution for stock returns, and thus towards the tail modeling based on EVT among financial researchers as well as market participants, is based on the stylized facts of the cross section of stock returns as in Bekaert, Erb, Harvey and Viskanta (1998) and Harris and Kucukozmen (2001). The specified studies all extract the issue of leptokurtosis, including non-normal fat tails in the cross section of stock returns. This fat tail

[2]See Hansen & Lunde (2005) for an extensive review of GARCH model types. The characteristics of different GARCH models are beyond the scope of the present study.

issue is especially relevant for REIT return data, since the specified asset class shows even stronger excess kurtosis in the daily return distributions, in comparison to the broader equity market (Fritz & Oertel, 2020). Consequently, fat tails are directly relevant from a practical point of view, because they lead to false risk-metric calculation (Dittmar, 2002). The alternative risk-metric calculation based on EVT models has been shown to entail empirical advantages in comparison to classical methods (Chavez-Demoulin, Embrechts & Hofert, 2016).

From an economic perspective, the heavy losses in the fat tails of the daily return distributions of REITs are a result of the non-normality of the underlying direct real estate positions (e.g. Byrne & Lee, 1997). The underlying assets are considered as the main driver for return movements of public equities from a valuation-based point of view. Rational investors, who are valuing REITs by means of a fundamental valuation approach, translate information about the net asset values (NAV) of the underlying assets into return movements of the stock price (Woltering, Weis, Schindler & Sebastian, 2018). Consequently, Rossignolo, Fethi and Shaban (2012) explicitly advise the application of return risk models, which are not based on the assumption of normally distributed returns. The following section on dynamic EVT regression represents one of these methodological alternatives, as called for in the study of Rossignolo, Fethi and Shaban (2012).

3.4 The Dynamic Extreme Value Regression Model

EVT regression specifications model the extreme events of a time series using EVT distributions, and explicitly not moments of the entire return distribution. In order to define these extreme events of a time series, either the block maxima or the peak over threshold (POT) method can be applied. We choose to apply the latter, since it is advantageous in terms of extreme data point generation (noted in general by Chavez-Demoulin, Embrechts & Hofert, 2016; Karmakar, 2017). Therefore, we let $u \geq 0$ be the threshold.

The return time series points, which exceed u, are treated as random exceedances $X_1, \ldots, X_q$, with corresponding excesses $Y_i = X_i - u, \quad i \in \{1, \ldots, n\}$. For financial returns, it is important to highlight, that this procedure is applied to the losses of a time series. The threshold is commonly chosen as a sufficiently low α-quantile of the return distribution. Nonetheless, the term sufficiency is debatable in this context (Karmakar, 2017), without a clear criterion for threshold selection. For the empirical study, the 25% quantile is selected. In any case, the vector containing the excesses Y_i yields only the α percent heaviest losses of the return distribution. As pointed out by Embrechts, Kluppelberg and Mikosch (1997), the number of exceedances until period t, N_t follows a Poisson process with intensity parameter λ, namely $N_t \quad Poi(\Lambda(t))$ with integrated rate function $\Lambda(t) = \lambda\, t$. Accordingly, and in line with the Balkema-de Haan-Pickands theorem (see McNeil, Frey & Embrechts, 2005 for a detailed reproduction), the distribution function of the excesses Y_i can be characterized by a GPD(ξ, β):

$$P\left(Y > y \mid Y > u\right) = G_{\xi,\beta}\left(y\right) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}}, \xi \neq 0 \\ 1 - \exp\left(-\frac{y}{\beta}\right), \xi = 0 \end{cases} \tag{3.5}$$

where ξ represents the scale and β the shape parameter, as $y \geq 0$ if $\xi \geq 0$ and $0 \leq y \leq -\beta/\xi$ if $\xi < 0$ applies.[3] Under asymptotic independence of the exceedance number N_t the maximization problem of the likelihood function can be formulated as:

$$L(\lambda, \xi,\ \beta; \Upsilon) = \frac{(\lambda T)^n}{n!} e^{(-\lambda T)\prod_{i=1}^{n} g_{\xi,\beta}(\Upsilon_i)} \tag{3.6}$$

where $g_{\xi,\beta}$ denotes the density of $G_{\xi,\beta}$. The decisive model Log-Likelihood can be split into two components, namely the Log-Likelihood for the number of exceedances as well as the excesses. The Log-Likelihood to be maximized follows:

$$\ell(\lambda, \xi,\ \beta; \Upsilon) = \ell(\lambda; \Upsilon) + \ell(\xi,\ \beta; \Upsilon) \tag{3.7}$$

with

$$\ell(\lambda; \Upsilon = \ -\lambda\ T + nlog(\lambda) + \log(\frac{T^n}{n!}) \tag{3.8}$$

and

$$\ell\left(\xi,\ \beta; \Upsilon\right) = \ \sum_{i=1}^{n} \ell\left(\xi,\ \beta; y\right) \tag{3.9}$$

with

$$l\left(\xi,\ \beta; y\right) = log_{g_{\xi,\beta}}\left(y\right) = \begin{cases} -\log\left(\beta\right) - 1\left(1 + \frac{1}{\xi}\right)\log\left(1 + \frac{\xi_y}{\beta}\right),\quad if\ \xi\ > 0,\ y \geq 0 \\ log(\beta) - \frac{y}{\beta},\ if\ \xi = 0 \\ -\infty,\quad otherwise. \end{cases} \tag{3.10}$$

The Log-Likelihood function is decisive for dynamic EVT models, because the model evaluation can only be based on the entire model likelihood and graphical inspection of the model residuals, which are asymptotically unit exponentially distributed

[3] If $\xi > 0$ applies, the mathematical condition needed for the specified asymptotics to hold is called regular variation. See Chavez-Demoulin, Embrechts and Hofert (2016) for a detailed proof. Financial return data can be assumed to satisfy $\xi > 0$, and thus to be analyzed by the outlined asymptotics.

(Chavez-Demoulin, Embrechts & Hofert, 2016). A familiar inference approach based on individual parameter significance, as known from ordinary least squares estimations and beta coefficients, does not exist for EVT models. Thus far, the described methodology represents the classic univariate EVT model for estimating the parameters of a GPD for the tail of a distribution, without additional information from exogenous covariates. By contrast, the dynamic multivariate regression model allows the dependence of GPD parameters on these exogenous covariates. Accordingly, we let the EVT distribution parameters vary conditional on exogenous covariates, including $\eta \in \mathbb{R}^p$ as the vector of parameters for the respective EVT distribution ($p = 2$ for a GPD):

$$g_k(\theta_k) = f_k(x_k) + h_k(t), \quad k \in (1, \ldots, p) \tag{3.11}$$

where g_k denotes a link function for the parameters, f_k the function for the covariate x_k, as well as h_k to model the behavior of g_k across time. The incorporation of covariates in θ is in line with the risk factors in CAPM or GARCH models. Thus, we transfer the logic of risk factors in conditional mean and variance models towards conditional EVT tail risk models. It should be emphasized, that the functional form of f_k can be open to discussion. Based on the pioneering work of Coles (2001), the original approach to EVT regression models used to be fully parametric. However, we chose a generalized additive model (GAM) for the functions in a non-parametric estimation of the link function, as introduced by Hastie and Tibshirani (1990), using penalized splines. The smoothing parameter selection of the GAM is subject to the Kullback-Leibler divergence equation (see Simonoff & Tsai, 1999 for an extensive reproduction). The non-parametric approach ensures greater flexibility of the functional relationship between the covariates and the dependent REIT return excesses (in line with Bee, Dupuis & Trapin, 2019). This is especially important, since literature relates directly to the present study in the field of EVT regression of REIT returns, which states a potential relationship form as orientation. The full dynamic multivariate EVT model then essentially re-parameterizes the estimates for the GPD parameters like β by ν, defined as:

$$\nu = \log[(1 + \xi)\beta)] \tag{3.12}$$

Accordingly, the re-parameterized Log-Likelihood for the excesses, denoted by ℓ^r follows:

$$\ell^r(\xi, \nu;\ \Upsilon) = \ \ell(\xi, e^{(\nu/1+\xi)}; \Upsilon) \tag{3.13}$$

Decisively, the functions for ξ and ν are now assumed to be a function of exogenous covariates x and time t, in order to capture the dynamics in the non-parametric form of equation 3.11:

$$\xi = \ \xi(x, t) = f_\xi(x) + h_\xi(t), \tag{3.14}$$

$$\nu = \ \nu\left(x,t\right) = f_{\nu}\left(x\right) + h_{\nu}\left(t\right), \tag{3.15}$$

The re-parameterized estimates of ξ and ν in equation 3.14 and 3.15 above are then incorporated into an equation for β:

$$\beta = \beta(x,t) = \frac{e^{\nu(x,t)}}{1+\xi(x,t)} \tag{3.16}$$

Since ξ and ν depend on exogenous covariates, $\xi\left(x,t\right)$ and $\nu\left(x,t\right)$ in equations 3.14 and 3.15 directly show the relationship between the estimated functions of the factor levels for $\widehat{f_{\xi}}, \widehat{h_{\xi}}, \widehat{f_{\nu}}$ and $\widehat{h_{\nu}}$ and the re-parameterized Log-Likelihood as the goodness of fit criterion of the model in equation 3.13. The expression of equation 3.16 leads to the re-parameterized estimate of β for describing the distribution function in equation 3.5. If covariates yield valuable explanatory power for the tail of the modeled REIT return series, the re-parameterized ξ and ν will decrease the informational loss, measured by the Log-Likelihood ℓ^{r}. The presented model parameters are estimated by a penalized maximum likelihood estimator including a backfitting algorithm (in line with Chavez-Demoulin, Embrechts & Hofert, 2016). Given these relationships and the description of the functional form of the model, the ultimate goal is the selection of statistically significant covariates to improve the goodness of fit criterions of the GPD models. The logically ensuing question is the identification of potential covariates let the parameters of the GPD and thus the tail risk model to be affected by. To do so, the following section reviews the empirical literature on exogenous covariates, which represent potential REIT tail risk factors.

3.5 Identification of REIT Tail Risk Factors as Model Covariates

For decades, researchers have examined the data-generating process of REIT returns and by doing so identified and described many corresponding risk and return factors using various empirical methods and analytical approaches. The field of extreme value modeling, on the other hand, is relatively young and there are as yet no empirical research results specifically on REITs. For the first attempt at such multivariate EVT modeling in the REIT domain, we essentially test the impact of covariates already known from other types of statistical models on the tail parameters. These statistical models cover those from section 3.3, namely multifactor specifications for modeling conditional means and secondly, conditional variance based on GARCH specifications. As we are utilizing daily REIT index return data, we focus on the identification of covariates for which such daily data is available, and do not consider some of the variables frequently studied in the literature, for which data is available on a monthly or weekly basis only. For a more wide-ranging compilation of the extensive literature on REIT risk and return, see the recent work of Letdin, Sirmans, Sirmans and Zietz (2019). We firstly focus on reproducing the factors which capture conditional mean, and then conditional variance.

Thirty years ago, Chan, Hendershott and Sanders (1990) employed a multifactor asset pricing model to show that a set of financial risk factors is significant and in part, consistent driver of REIT returns. They found the risk structure and the term structure of the bond market to be key factors driving both equity market and REIT returns. Subsequent work, most of which shares the common ground of integrating the dependencies between REIT returns, stock and bond markets, has adopted macro-factor approaches and included multiple further variables to study REIT return behavior (Ling & Naranjo, 1997; Ling & Naranjo, 1999; Ling, Naranjo & Ryngaert, 2000). Clayton and MacKinnon (2001) investigate the time variability of the link between REIT returns, direct real estate returns, large cap and small cap stock returns and bond returns, in a multi-factor model. They find that REIT returns have a higher sensitivity to small cap stock than to large cap stock. In a follow-up study, Clayton and MacKinnon (2003) find that this relationship is time-variant.

Glascock, Lu and So (2000) show that REITs behave more like stocks and less like bonds. Similarly, both pre-financial crisis studies that were conducted for example by Ross and Zisler (1991), Gyourko and Keim (1992) or Liu and Mei (1992), and more recent studies that include the liquidity crisis of 2008/2009 in their analysis like Huang, Wu, Liu and Wu (2016) or Liow, Zhou and Qing (2015), demonstrate that stock price indices exhibit significant positive relationships with REIT returns.

Changes in monetary policy refer to the actions that the US Federal Reserve takes to influence the availability and cost of money (Ewing & Payne, 2005). Studies that proxy for monetary policy, and that find a significant impact thereof on real estate returns, mostly either use changes in money supply/monetary base (Darrat & Glascock, 1989; Ling, Naranjo & Ryngaert, 2000) or changes in the federal funds rate (FFR) (Ewing & Payne, 2005; Bredin, O'Reilly & Stevenson, 2007; Chen, Peng, Shyu & Zeng, 2012). According to Chang, Chen and Leung (2011), equity REIT (EREIT) and housing market returns have a significant non-linearity with the FFR and term spread. Using quantile regression, Chen, Peng, Shyu and Zen (2012) also investigate the effects of changes in monetary policy proxied by the FFR on securitized real estate returns. They show that the effect of changes in monetary policy is conditional upon market state. In volatile bear markets, changes in monetary policy have no effect on returns, while during bull markets, changes in monetary policy have a significant adverse effect on EREIT returns.

A common proxy for investor sentiment in the general stock market is the Chicago Board of Options Exchange (CBOE) volatility index (VIX) (Conolly, Stivers & Sun, 2007; Freybote, 2016; Anoruo & Murthy, 2017). The VIX measures implied volatilities based on S&P500 options and by so doing, captures the expectations of investors about future market volatility. Hence, the greater the VIX, the higher the volatility due to sentiment and uncertainty. In a study on distress-risk and stock returns, Shen (2020) finds that the distress-risk anomaly of EREIT returns is highly correlated with the VIX. Lin, Rahman & Yung (2009) show, in a mean regression approach, that when investors are optimistic, REIT returns increase and when they are pessimistic, they become lower, when including conventional control variables like term and risk structure.

Turning to REIT return characteristics from a conditional variance perspective, using GARCH and EGARCH specifications on monthly data to investigate volatility spillovers, Stevenson (2002) finds that REIT return volatility is influenced more strongly by volatility in small cap stocks than by large cap stocks or US bonds, which is in line with the early findings of Giliberto (1993). Further research found certain macro-variables such as long-run interest rate, short-run interest (West & Worthington, 2006), the FFR (Jirasakuldech, Campbell & Emekter, 2009) and the risk premium and term structure in the bond market (Fei, Ding & Deng, 2010) to be drivers of REIT return volatility.

Given the above discussion, in the present study we consider returns in the general stock market for small cap and large cap stock, term spreads, risk spreads, the FFR and the VIX as the covariates to investigate. In mathematical terms, these variables represent the covariates x in equations 3.14 and 3.15 for $\xi(x,t)$ and $\nu(x,t)$. Work such as Clayton and MacKinnon (2003), which underlines the time-variance of relationships, legitimize the additional dependence of ξ and ν on time (t). However, we do not claim that these variables capture all relevant risks that affect the tail parameters of the investigated REIT returns. Nevertheless, there is evidence that especially financial market data can proxy for a reasonable portion of tail risk exposure determining asset returns and are therefore suited for further analyzing tail risk parameter movement.

3.6 Data Set and Descriptive Statistics

The dependent securitized real estate data represents daily returns of closing price returns of the FTSE EPRA/NAREIT US indices, collected from Thomson Reuters Eikon. We gather observations for various usage types by generating returns for EREITS, including the NAREIT All Equity, Office, Retail, Industrial, Residential REIT indices and with regard to mortgage REITs (MREIT), the NAREIT MREITs index alongside the Mortgage Commercial and Mortgage Home Financing indices. Additionally, the combined All REITs index is used, leading to a total number of eight REIT indices as the dependent. We use several indices to test for potential heterogeneity of the covariates on the different indices, especially since the exogenous covariates are themselves equity and debt market proxies, potentially affecting their REIT peer markets. The complete data set covers 2,966 observations per time series from July 2008 to July 2020, and thus a total number of 23,720 daily REIT returns. Missing return observations due to exceptional market closure events (such as 9/11) were set to zero.

We incorporate equity market data, by using daily closing price returns from the S&P500 index, to reflect the development of the most prominent public equity index in the US Additionally, daily returns from the S&P600 small cap index serve as an alternative proxy, to reproduce the return variation of equities with smaller market capitalization and thus higher financial similarity to most EREITs, as noted by Wang, Erickson and Chan (1995) or Stevenson (2002). We also use returns of the NASDAQ composite and the Dow Jones (DJ) Industrial, to test for other equity types so as to affect the lower tail of the dependent returns. Moreover, market volatility is captured by the daily changes in the VIX, obtained from the CBOE.

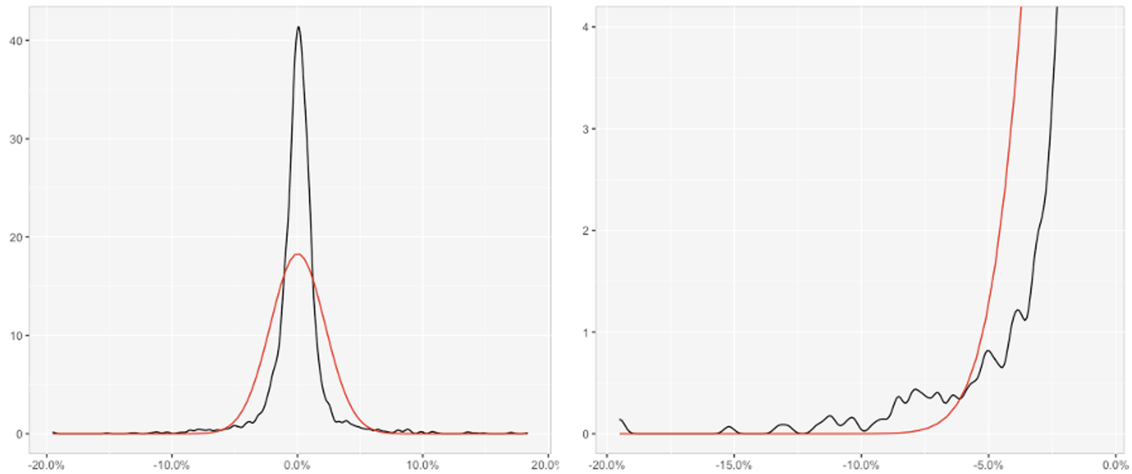
We also add explanatories from bond markets. Accordingly, we use the database on bond yields of the Federal Reserve Bank of St. Louis (FRED) and construct several daily yield changes. We formulate two versions of the term spread and two versions of the risk spread in the bond market since the studies listed in section 3.5 do not define them uniformly. Thus, we want to exploit this heterogeneity to test for a different sensitivity of the GPD parameters to variation in the calculation of these factors. Following Petkova (2006) and Glascock and Lu-Andrews (2014), we calculate the term structure as the daily changes in the premium between the ten-year and one-year government bond yields (TERM 1) and in line with Chan, Hendershott and Sanders (1990), as the daily changes in the premium between the ten-year and one-month government bond yields (TERM 2). Additionally, we construct the default risk premium as the daily change in the spread between Moody's Baa corporate bond index and the ten-year government bond yield (RISK 1), as also described by Chan, Hendershott and Sanders (1990), and as the daily change in the spread between Moody's Baa corporate bond index and Aaa corporate bond index (RISK 2), again following Glascock & Lu-Andrews (2014). Lastly, to proxy for interest rates and monetary policy we use the FFR. The VIX and the bond market yields and spreads are not treated as daily returns, but by calculating the daily percent change, denoted by $\Delta\ r_t = r_t - r_{t-1}$.

In addition to the constructional aspects of the data set, the optical and numerical univariate analysis of the data provides some first insights into the distributional characteristics of the data. In line with expectations due to the stylized facts of the return distribution from the related literature, we observe a typically leptokurtic empirical return distribution, including fat tails of the dependent variables of the present study (see Figure 3).[4]

For the lower tail of the All Equity price return index, we firstly observe extremely large losses in comparison to the normal distribution in absolute terms, observable in particular from the density mass below -10.0% of the empirical daily return distribution. Secondly, an excessive part of the distribution mass is located in the area of smaller absolute values for the exceedances, between daily returns of -5.0% and -10.0%. This empirical density closer to the threshold causes the shape parameters to be potentially close to zero, because smaller shape estimates allow for larger amounts of density closer to the threshold, holding the scale parameter constant. This variation of the density mass in the lower part of the exceedances clarifies the need to vary shape parameters of the GPDs across the different return series. With regard to the estimation problem of the parameters, potential explanatory covariates need to yield similar distributional return characteristics, in order to provide explanatory power to the GPD parameters of the dependents.

[4] The statement holds for all REIT indices in the data set.

Figure 3: Empirical distribution of the FTSE EPRA/NAREIT US All Equity index returns and fitted normal distribution



Notes: The left-hand plot displays the empirical return distribution (black line) in comparison to the theoretical normal distribution (red line). The right-hand graphic shows the lower tail of the distribution, cut off at the 25% quantile of the empirical distribution, which is also used as the threshold for the POT method.

These similarities of the distributional characteristics of the data can be numerically drawn from the descriptive statistics in Table 6 below. In sum, these characteristics reveal the expected division between the EREITs, stock market covariates and the VIX on one hand, and the remaining debt variables on the other. REIT indices show clearly separated first moments with regard to equity and debt positions, since EREITs unanimously display positive mean returns, whereas their debt peers collectively show negative first moments. These findings for EREITs are similar to their equity position peers from the broader stock market, because all equity indices of the sample show positive mean returns. The standard deviations (SD) of the distributions are more homogenous across the REIT indices in terms of absolute values. Interestingly, the second moment of the Mortgage Home Financing index represents an outlier with a significantly lower dispersion than its commercial mortgage peer and all equity REITs. The dispersion of the time series is also captured by the minima and maxima of the data. Here, the REITs display more extreme values than the broader stock market data. Especially the minima values are essentially interesting for the fit of the GPD, since a wider spread of the distribution into the lower tail cause the scale parameter of the GPD to be larger, in order to allow for more density in the very tail, holding the shape parameter constant.

The third moment yields mixed signs. Even though the majority of the REIT indices are positively skewed, the retail and especially the distribution of the Mortgage Home Financing index, as well all equity indices, are negatively skewed. The fourth moment and the additionally calculated excess kurtosis of the distributions support the assumption of heavily leptokurtic and fat-tailed return distributions. These characteristics are also expressed by the reported Jarque-Bera-Test statistic (JB), which unanimously rejects the assumption of normal distribution. Additionally, the test for serial autocorrelation ($Q(16)$) of the original time series, as well as the squared residuals ($Q^2(16)$), yield empirical evidence of the existence of serial autocorrelation in the data. In sum, these descriptive statistics confirm the stylized facts about financial return data in the literature, refuting the assumption of normality, and thus numerically support the application of EVT distributions for the tail. For the deeper numerical analysis of the lower tail of interest, we report the quantiles at the one, five and ten percent levels, as well as the interquartile range (IQR) between the zero (or minima respectively) and the 10% and 25% level quantiles. The 1% quantiles for all REITs are significantly larger than for the covariates, whereas the results for the 5% and 10% quantiles are mixed. Thus, we conclude that the REIT data requires a more disperse GPD and potentially increasing scale and lowering shape. This pattern also holds true for the reported IQRs.

Table 6 Descriptive statistics of the data set

	N	Mean	Median	SD	Min.	Max.	Skew.	Kurt.	Exc. Kurt.	1st.%	5th.%	10th.%	IQR25	IQR10	JB	Q(16)	$Q(16)^2$
All Equity	2,966	0.029	0.081	2.178	-19.498	18.351	0.035	20.276	17.276	-7.456	-2.650	-1.650	18.875	17.848	36,885	177	5,188
Residential	2,966	0.046	0.084	2.182	-19.166	18.291	0.104	19.424	16.424	-6.997	-2.636	-1.792	18.542	17.374	33,340	177	5,322
Office	2,966	0.027	0.055	2.288	-22.021	20.326	0.171	21.428	18.428	-7.546	-2.842	-1.731	21.375	20.290	41,981	187	4,723
Retail	2,966	0.016	0.074	2.405	-23.883	21.551	-0.015	22.256	19.256	-8.406	-2.920	-1.861	23.172	22.022	45,822	137	3,917
Industrial	2,966	0.059	0.100	2.864	-27.475	29.424	0.040	24.794	21.794	-9.572	-3.275	-1.964	26.724	25.511	58,703	213	7,380
Mortgage REITs	2,966	-0.008	0.000	1.873	-23.625	21.097	0.022	38.388	35.388	-5.687	-2.161	-1.351	23.097	22.273	15,4767	129	4,326
Mortgage Home	2,966	-0.012	0.053	1.871	-24.797	21.764	-0.141	40.362	37.362	-5.396	-2.246	-1.408	24.283	23.389	17,2520	143	3,811
Mortgage Commercial	2,966	-0.012	0.051	2.645	-23.906	29.066	0.497	28.954	25.954	-8.920	-3.157	-1.759	23.280	22.147	83,368	98	3,097
All REITs	2,966	0.031	0.085	2.066	-18.570	17.629	0.097	20.697	17.697	-7.270	-2.459	-1.527	18.005	17.043	38,711	188	5,296
S&P500	2,966	0.042	0.067	1.328	-11.984	11.580	-0.259	17.032	14.032	-4.199	-1.948	-1.189	11.608	10.795	24,365	149	4,054
S&P600	2,966	0.040	0.083	1.625	-13.247	9.007	-0.477	11.154	8.154	-4.862	-2.350	-1.569	12.608	11.678	8,330	110	4,634
NASDAQ	2,966	0.073	0.117	1.420	-12.193	12.580	-0.124	13.883	10.883	-4.075	-2.213	-1.396	11.754	10.797	14,645	159	3,150
DJ Industrial	2,966	0.038	0.057	1.277	-12.927	11.365	-0.151	19.617	16.617	-3.890	-1.822	-1.132	12.541	11.795	34,136	183	4,020
VIX	2,966	-0.002	-0.100	2.113	-17.640	24.860	1.613	28.111	25.111	-5.478	-2.578	-1.685	16.880	15.955	79,211	137	1,725
FFR	2,966	-0.001	0.000	0.052	-0.880	1.010	-1.905	183.804	180.804	-0.090	-0.018	-0.010	0.880	0.870	4,041,761	1002	3,749
TERM 1	2,966	0.000	0.000	0.051	-0.420	0.300	-0.146	8.350	5.350	-0.130	-0.080	-0.060	0.390	0.360	3548	26	732
TERM 2	2,966	-0.001	0.000	0.064	-0.620	0.420	-0.428	11.827	8.827	-0.170	-0.090	-0.070	0.580	0.550	9720	77	919
RISK 1	2,966	0.000	0.000	0.032	-0.200	0.380	2.460	30.344	27.344	-0.080	-0.048	-0.030	0.190	0.170	95,393	836	1,012
RISK 2	2,966	0.000	0.000	0.027	-0.300	0.470	2.382	56.552	53.552	-0.070	-0.040	-0.020	0.290	0.280	357,215	268	675

Source: Own Calculation.

In addition to the univariate analysis of the time series data, we are interested in the bivariate analysis and the dependence structure of the data, because inductive regression models are generally based on co-movement investigation. However, since we are modeling the lower tails of the distribution using the POT approach, we refrain from analyzing the classic Bravais-Pearson correlation matrix, because the named metric reflects the pairwise linear dependence across the entire bivariate distribution of the variables.[5] Instead, we use a pairwise lower-tail dependence coefficient λ_L below the same threshold at the 25% quantile, to extract statements about the co-movement structure specifically in the tail of the distribution (see Table 7).[6]

Most importantly, we analyze the lower tail-dependence of the target REIT returns and the explanatories (see table 7). The lower tail-dependence coefficients of the EREIT returns range above 0.5 with regard to all equity market explanatories, indicating a potentially higher informational power of these variables in comparison to the bond market variables. The latter variable category shows lower absolute tail-dependence coefficients, which indicates a less clear bivariate co-movement. Interestingly, the VIX shows small absolute values for the lower tail-dependence coefficients (around 0.1). Thus, the VIX appears not to clearly co-move towards the tail with any REIT or equity position of the data set. This finding, however, is in line with the construction logic of the VIX, since it captures two-sided volatility from equity options and not specifically tail risk. The only variable to contradict this low tail-dependence of the VIX is the FFR. Remarkably, the FFR is also highly tail-dependent on all REIT and equity positions as the only debt market variable of the data set. Thus, the FFR appears to be the potentially most impactful GPD covariate among the bond market proxies. Economically, this bivariate relationship can potentially be justified by the typically high leverage levels of REITs, which are highly exposed to interest rate risk in consequence. By contrast, other classic bond market risk proxies appear to display less clear tail-dependence. This finding indicates that REIT returns could be more exposed in the tail to federal debt conditions than to the corporate debt market conditions. In sum, the univariate and bivariate analyses support the assumption of REIT and equity market returns being highly dependent, also with regard to the lower tail. Bond market proxies generally lack dispersion from an univariate point of view and additionally show smaller lower tail dependence than the equity market covariates (with exception of the FFR). However, the univariate description and the numerical analysis of the time series does not fully disclose the potential impact of the covariates in a GAM for GPD parameters, which are reported in the following section.

[5] The well-known Bravais-Pearson correlation coefficients can be found in the appendix.

[6] The lower tail dependence coefficient for a pair of random variables X_1, X_2 is defined by: $\lambda_L = \lim_{u \downarrow 0^+} P(F(X_1) \leq u \mid G(X_2) \leq u)$ as presented by e.g. Embrechts, Hofert and Wang (2016).

Table 7 Pairwise lower tail-dependence coefficient matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	**All Equity**	1																	
(2)	**Residential**	0.848	1																
(3)	**Office**	0.872	0.768	1															
(4)	**Retail**	0.869	0.771	0.808	1														
(5)	**Industrial**	0.808	0.741	0.771	0.744	1													
(6)	**Mortgage REITs**	0.582	0.552	0.596	0.560	0.567	1												
(7)	**Mortgage Home**	0.561	0.537	0.572	0.544	0.540	0.934	1											
(8)	**Mortgage Comm.**	0.614	0.571	0.625	0.575	0.619	0.692	0.641	1										
(9)	**All REITs**	0.951	0.834	0.865	0.856	0.806	0.606	0.584	0.630	1									
(10)	**S&P500**	0.605	0.543	0.623	0.578	0.609	0.549	0.520	0.621	0.622	1								
(11)	**S&P600**	0.610	0.541	0.636	0.583	0.605	0.561	0.528	0.661	0.632	0.788	1							
(12)	**NASDAQ**	0.551	0.502	0.565	0.529	0.556	0.506	0.483	0.579	0.571	0.811	0.713	1						
(13)	**DJ Industrial**	0.583	0.528	0.596	0.563	0.586	0.532	0.503	0.598	0.601	0.888	0.748	0.745	1					
(14)	**VIX**	0.093	0.111	0.089	0.109	0.094	0.120	0.126	0.101	0.084	0.028	0.038	0.035	0.030	1				
(15)	**FFR**	0.517	0.522	0.510	0.511	0.529	0.526	0.516	0.514	0.521	0.521	0.511	0.516	0.528	0.495	1			
(16)	**TERM 1**	0.336	0.336	0.362	0.336	0.362	0.317	0.310	0.381	0.347	0.462	0.441	0.432	0.466	0.155	0.511	1		
(17)	**TERM 2**	0.333	0.332	0.355	0.337	0.355	0.329	0.318	0.375	0.344	0.460	0.448	0.426	0.472	0.151	0.505	0.737	1	
(18)	**RISK 1**	0.244	0.263	0.236	0.248	0.219	0.255	0.259	0.242	0.242	0.200	0.216	0.205	0.190	0.304	0.529	0.186	0.169	1
(19)	**RISK 2**	0.278	0.283	0.279	0.277	0.273	0.256	0.252	0.274	0.278	0.282	0.283	0.267	0.281	0.279	0.507	0.252	0.248	0.402

Source: Own Calculation.

3.7 Empirical Findings and Model Diagnostics

The procedure for testing the statistical significance of the investigated covariates is based on the equation set of Chavez-Demoulin, Embrechts and Hofert (2016). Essentially, we estimate each line of equations below, and then compare the Log-likelihoods of these models against each other, in line with Kiriliouk, Rootzén, Segers and Wadsworth (2019). Firstly, we estimate the benchmark univariate GPD models without exogenous covariates, and only the constant terms c_ξ or c_ν based on equation 3.17 below. We then incorporate the single market covariate of interest into the equations as x to let ξ and/or ν to depend on in addition to linear, $c_\nu\,(t)$, or non-linear, $h_\nu\,(t)$, time effects (models of equation 3.18 through 3.22):

$$\xi\ \ (x,t) = c_\xi \quad ; \quad \nu\ \ (x,t) = c_\nu \tag{3.17}$$

$$\xi\ \ (x,t) = f_{\xi\ (x)} \quad ; \quad \nu\ \ (x,t) = c_\nu \tag{3.18}$$

$$\xi\ \ (x,t) = f_{\xi\ (x)} + c_{\xi\ (t)} \quad ; \quad \nu\ \ (x,t) = c_\nu \tag{3.19}$$

$$\xi\ \ (x,t) = f_{\xi\ (x)} \quad ; \quad \nu\ \ (x,t) = f_{\nu\ (x)} \tag{3.20}$$

$$\xi\ \ (x,t) = f_{\xi\ (x)} \quad ; \quad \nu\ \ (x,t) = f_{\nu\ (x)} + c_{\nu\ (t)} \tag{3.21}$$

$$\xi\ \ (x,t) = f_{\xi\ (x)} \quad ; \quad \nu\ \ (x,t) = f_{\nu\ (x)} + h_{\nu\ (t)} \tag{3.22}$$

The comparison of the goodness of fit for model 3.17 and 3.18 is suitable for assessing the significance of the included covariate x on ξ, captured by $f_{\xi(x)}$. A comparison of models 3.18 and 3.19 indicates an additional potential dynamic effect of time on ξ. The assessment of models 3.18 versus 3.20 shows the significance of the covariate on ν. The comparison of models 3.20 and 3.21 indicates the impact of the linear time effect on ν. A separation of the models 3.21 and 3.22 is used to assess whether the time metric exerts a linear or non-linear effect on ν. We set the threshold u for the POT estimation at the 25% quantile of the return distribution, to model a sufficient number of losses as the lower tail. The sensitivity of the results with respect to the threshold selection can be debatable (see Caeiro & Gomes, 2016 for a thorough discussion).

However, we do not vary the threshold explicitly, but report the effect of threshold selection for a single exemplary time series as part of the model diagnostics, using the corresponding test. We also do not explicitly report the estimated re-parameterized values for ξ and ν, because the actual estimates do not contain information about the statistical significance of the relationship between the GPD parameters and the

Table 8 Thresholds, Anderson-Darling statistics and Log-Likelihoods of benchmark models of equation 3.17

	All Equity	Resi-dential	Office	Retail	Indus-trial	Mortgage REITs	Mortgage Home	Mortgage Commercial	All REITs
Threshold u	-0.622	-0.624	-0.646	-0.711	-0.751	-0.527	-0.515	-0.626	-0.565
N below	742	742	742	742	742	742	742	742	742
AD statistic	0.542	0.730	0.512	0.406	0.255	0.805	0.432	0.975	0.598
AD p-value	0.228	0.100	0.259	0.433	0.789	0.066	0.389	0.026	0.174
Log-L model (3.17)	-992.2	-1007.3	-1020.9	-1063.1	-1145.3	-825.1	-859.4	-1088.6	-953.2

Notes: The table reports the absolute value of the corresponding loss for the threshold selection. We observe 742 losses below the reported threshold. Additionally, the AD test statistic including the p-value is reported to justify the assumption of a uniform distribution of the observations below the threshold. Lastly, the benchmark model Log-Likelihood is displayed.

exogenous covariates. Table 8 contains the Log-Likelihood for each of the benchmark models of equation 3.17 and the thresholds for all indices, as well as the Anderson Darling (AD) statistic and corresponding p-value of the AD test for a GPD fit. The AD can be used to confirm the choice of threshold, according to the procedure of Choulakian and Stephens (2012) for checking the asymptotic uniform distribution.

The first assessment of the benchmark models reveals the general feasibility of all time series as a model of a univariate GPD, because the p-values of the AD test demonstrate sufficient confidence in the fit of a GPD for the majority of the time series ($p > 0.01$). The only notable outliers, rejecting the null hypothesis of a GPD fit of the data to some extent, represent the Mortgage REITs index at the 10% confidence level and the Mortgage Commercial time series at the respective 5% level. Interestingly, this finding illustrates the generally lower feasibility of a GPD fit for MREIT return tails in comparison to their EREIT peers. Turning to the actual multivariate EVT model study, the ensuing tables reproduce the Log-Likelihood of the equation set specified above for each investigated covariate, and model specifications 3.18 to 3.22, as well as the Log-Likelihood of the benchmark model of equation 3.17 without an exogenous covariate (see Table 9):

For the exogenous covariates from equity markets, we extract several insights. Firstly, and most importantly, we observe the general applicability of exogenous equity market covariates. We derive this finding from the fact that all tails of the dependent REIT indices show on average lower Log-Likelihoods for model fits with model equation 3.18 through 3.22 in comparison to the benchmark model with equation 3.17. Secondly, we find little empirical evidence for the benefit of the inclusion of exogenous equity market covariates solely in the estimation of ξ. Generally, model fits using equation 3.18 do not outperform the benchmark for any dependent REIT index. In contrast, a large reduction in informational loss can be observed for the comparison of the goodness of fit measures for models 3.18 and 3.19 with model 3.20, and thus for the inclusion of exogenous covariates for ν. Unlike for model 3.18, we find consistent outperformance of model 3.20 in comparison to the benchmark for all

Table 9 Log-Likelihoods for models with exogenous equity market covariates

	All Equity	Resi-dential	Office	Retail	Indus-trial	Mortgage REITs	Mortgage Home	Mortgage Commercial	All REITs
Benchmark									
Model (3.17)	-992.2	-1007.3	-1020.9	-1063.1	-1145.3	-825.1	-859.4	-1088.6	-953.2
S&P500									
Model (3.18)	-998.0	-1010.0	-1033.1	-1065.4	-1169.9	-819.0	-845.9	-Inf	-959.4
Model (3.19)	-967.2	-985.9	-1000.1	-1042.2	-1122.5	-797.5	-832.0	-1070.7	-926.9
Model (3.20)	-823.6	-875.6	-864.3	-963.7	-1037.4	-726.6	-767.5	-1025.3	-773.1
Model (3.21)	-825.8	-864.3	-859.2	-935.6	-997.8	-725.6	-766.9	-Inf	-773.2
Model (3.22)	-750.9	-786.3	-777.5	-863.5	-884.3	-689.6	-733.4	-853.2	-Inf
S&P600									
Model (3.18)	-990.1	-1004.2	-1024.4	-1057.0	-1159.4	-820.8	-847.6	-Inf	-951.6
Model (3.19)	-962.3	-982.9	-992.3	-1035.7	-1121.2	-793.3	-828.7	-1065.9	-923.3
Model (3.20)	-805.7	-860.1	-834.3	-918.7	-1026.6	-702.5	-750.2	-975.3	-764.9
Model (3.21)	-807.4	-851.7	-836.6	-900.4	-984.9	-699.7	-750.1	-954.0	-766.1
Model (3.22)	-744.4	-788.5	-767.7	-840.3	-883.0	-673.3	-719.9	-837.6	-704.9
NASDAQ									
Model (3.18)	-1001.3	-1014.1	-1037.3	-1068.6	-1167.5	-834.3	-859.8	-Inf	-964.0
Model (3.19)	-973.3	-991.8	-1005.4	-1045.3	-1126.4	-803.2	-838.3	-1073.7	-934.6
Model (3.20)	-875.8	-912.0	-930.1	-1004.5	-1079.2	-757.9	-795.2	-1076.6	-825.2
Model (3.21)	-865.6	-896.1	-910.1	-969.3	-1020.8	-757.9	-793.3	-Inf	-821.4
Model (3.22)	-781.4	-Inf	-813.6	-895.4	-910.6	-707.4	-749.7	-876.4	-732.8
DJ-Industrial									
Model (3.18)	-1001.9	-1012.8	-1037.2	-1069.1	-1176.0	-816.1	-843.1	-Inf	-963.5
Model (3.19)	-970.1	-987.5	-1002.7	-1044.6	-1127.8	-797.0	-831.1	-1072.5	-930.2
Model (3.20)	-842.6	-887.7	-880.8	-974.5	-1073.1	-721.3	-764.4	-1042.9	-789.8
Model (3.21)	-842.0	-874.6	-874.0	-945.1	-1023.0	-720.1	-764.4	-999.2	-791.4
Model (3.22)	-758.7	-789.2	-783.8	-Inf	-899.6	-687.2	-731.0	-863.5	-709.1
VIX									
Model (3.18)	-1022.5	-1032.3	-1055.7	-1093.7	-1194.0	-864.7	-890.6	-Inf	-983.9
Model (3.19)	-982.5	-999.0	-1012.7	-1055.4	-1137.7	-809.6	-844.3	-1082.0	-942.3
Model (3.20)	-943.3	-975.5	-985.1	-1077.5	-1209.0	-797.8	-838.3	-1171.6	-883.9
Model (3.21)	-928.5	-950.3	-963.7	-1020.6	-1105.9	-796.3	-833.4	-1089.0	-882.0
Model (3.22)	-804.5	-828.3	-830.1	-907.9	-957.2	-713.3	-754.7	-902.5	-754.0

Notes: The table shows the Log-Likelihood of the equation set from Chavez-Demoulin, Embrechts and Hofert (2016). The benchmark model based on equation (3.17) is only displayed once, because the Log-Likelihood of it is the same across all covariates. The value "-Inf" indicates the impossibility of fitting the GPD on the tail for a given covariate and model equation.

studied covariates. Hence, it can be concluded that the multivariate modeling of ν is more beneficial than for ξ for equity market covariates. This finding is in line with the remark about the relative importance of both GPD parameters from Chavez-Demoulin, Embrechts and Hofert (2016), who find similar results for their data by stressing the importance of an exogenous modeling of ν. This empirical insight can be explained by the probability density of the return series close to the threshold. These excesses with small absolute values are mainly captured by variations of ν instead of ξ.

Among the covariates, we find that the S&P600 proxy appears to be the most powerful covariate to include in the models (except for the residential equity REIT time series). This finding is in line with the literature on conditional mean and variance models, which favors the explanatory power of small cap equity proxies like the S&P600 in comparison to other large cap equity indices, as noted in the literature review for classic conditional moments (e.g. Stevenson, 2002; Clayton & MacKinnon, 2003). From those models of the S&P600 with a numerical solution for the Log-Likelihood, only the Office and Industrial REIT models are less powerful than the benchmark. A remarkably low explanatory power can be observed for the VIX. This result could have been anticipated with regard to the bivariate lower tail dependence matrix and can be explained by the construction of the VIX.

Across the REIT indices, we find heterogeneity among the empirical results for the equity market covariates. Firstly, we can confirm higher reductions in the Log-Likelihood for the EREITs than for the MREITs. This finding is generally in line with expectations, because EREITs are assumed to be more integrated into the broader equity market than their MREIT peers. Among EREITs we observe the largest reductions in Log-Likelihoods for the All Equity REIT time series by incorporating covariates, followed by the Office REIT index. A remarkably low explanatory power of the inclusion of equity market covariates can be observed on average for the Retail and Industrial EREIT series. These findings suggest a higher equity market integration of the tail of Office REITs compared to the Retail and Industrial REITs peers. Among the MREITs on the other hand, we find empirical evidence of the highest reductions in Log-Likelihood for the Commercial MREIT time series (except for the VIX). The reductions for the All REIT time series shows the highest Log-Likelihood reductions on average for all equity market covariates (except for the S&P500). This high explanatory power of the equity market covariates on the blended All REIT time series can be interpreted as indicating the highest equity market integration of the tail of the All REIT index.

Another highly important modeling aspect is the impact of the time function. For the linear time effects, we observe a moderate influence on the model fit, by comparing Log-Likelihoods of fits of model 3.21 with the benchmark Log-Likelihoods and those of models 3.18 to 3.20. However, we find a relatively small outperformance of fits with model equation 3.21 compared to fits with model equation 3.20 and thus conclude a significant effect of time on the REIT return tail modeling. This finding for the tail of the return series is in line with the widely known time variance of the entire REIT return series distribution, as well as its time varying volatility (e.g. Jirasakuldech, Campbell & Emekter, 2009) and time dependency of correlations between REIT returns and macro variables (e.g. Fei, Ding & Deng, 2010). A larger outperformance can be observed for the models which include a non-linear effect of time on ν, denoted by $h_\nu(t)$. The specified model 3.22 is the one with the lowest Log-Likelihood overall. We conclude that the time effects on the tail are clearly non-linear for the models with equity market covariates. We now turn to the model fits which include the debt market covariates (see Table 10).

As the first and overall finding for the debt market covariates, on average, we find smaller improvements in informational power in comparison to the equity market covariates. This is particularly surprising for the MREITs, because one would expect debt market covariates to contain more information about MREITs than the equity market. However, we do not observe this effect in our data. Instead, the equity covariates clearly outperform the debt market covariates across all studied REIT usage type indices. In sum, this finding shows that also the lower tail by itself and its moments are more cointegrated with stocks than with bonds, as has already been demonstrated empirically in conditional mean (e.g. Glascock, Lu & So, 2000) and conditional volatility settings (e.g. Stevenson, 2002). This tendency has also been found in the bivariate analysis of the lower tail dependence estimation in the previous section. The specified tail metric can thus be considered as a useful tool for preliminary analysis for a multivariate EVT regression model. Specifically, the debt market covariates do not display homogenous reductions in the Log-Likelihoods on average, like the exogenous equity market covariates across the model fits with equations 3.18 to 3.22. Instead, the average differences of the benchmark Log-Likelihoods and all fits with model specification 3.18 to 3.22 of the debt market covariates are not negative. This finding, however, is mainly driven by the poor performance of models 3.20 and 3.21. Fits with model equation 3.22 still unanimously outperform the benchmark model 3.17. This finding, however, casts doubt on the actual explanatory power of the debt market covariates themselves, because it is mainly the result of the non-linear time effect. Turning to the impact on the individual model parameters, the effects are ambiguous. As for the equity covariates, the inclusion of debt market covariates in the explanatories for the ξ parameter of REIT index losses actually decreases the goodness of fit of models 3.18 compared to the benchmark model. The linear time effect on ξ only provides rather small absolute Log-Likelihood reductions on average, comparing models 3.19 to 3.17. Model 3.20 without a time effect performs on average worse than the benchmark model 3.17, and also with regard to models 3.21 and 3.22. Thus, we see evidence countering the debt market covariates, because Log-Likelihood reductions are on average driven by the time factor of the models, as noted above. In sum, we conclude that the tail risk of REIT returns is dependent on equity market covariates instead of debt market variables.

The highest explanatory power among the covariates can be observed for the term spreads, followed by the FFR. Risk spreads perform significantly worse on average. With regard to potential term spread differences, we do not observe an effect of the term spread duration in our results. For the spread with respect to the one-year government bond yields (TERM 1), we find a very similar mean Log-Likelihood across all estimated models, as for the one-month (TERM 2) peer.

Table 10 Log-Likelihoods for models with exogenous debt market covariates

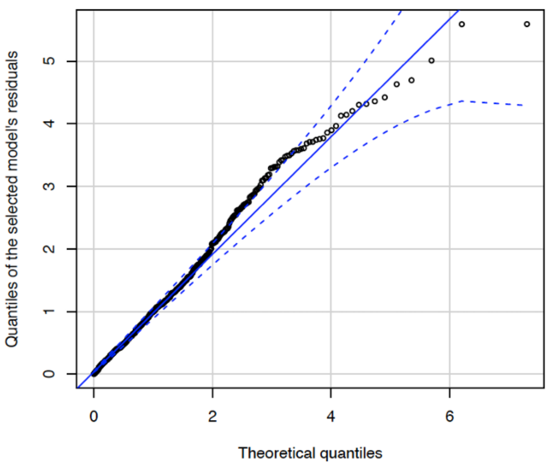
	All Equity	Resi-dential	Office	Retail	Indus-trial	Mortgage REITs	Mortgage Home	Mortgage Commercial	All REITs
Benchmark									
Model (3.17)	-992.2	-1007.3	-1020.9	-1063.1	-1145.3	-825.1	-859.4	-1088.6	-953.2
TERM 1									
Model (3.18)	-1036.5	-1039.2	-1068.5	-1102.3	-1212.7	-877.0	-899.1	-1169.8	-999.2
Model (3.19)	-991.1	-1006.0	-1019.6	-1062.2	-1144.7	-822.6	-855.2	-1087.3	-951.6
Model (3.20)	-1037.5	-1046.2	-1084.5	-1176.1	-1337.0	-842.1	-868.7	-1240.3	-985.5
Model (3.21)	-993.7	-1002.3	-1024.9	-1095.6	-1185.4	-836.5	-859.3	-1127.0	-954.6
Model (3.22)	-857.0	-875.8	-876.0	-965.4	-1046.5	-732.4	-765.2	-946.5	-811.2
TERM 2									
Model (3.18)	-1034.6	-1037.6	-1067.1	-1100.7	-1210.4	-876.1	-896.4	-1165.8	-997.1
Model (3.19)	-989.3	-1004.8	-1018.9	-1060.7	-1142.7	-822.2	-854.6	-1086.6	-950.0
Model (3.20)	-1026.9	-1042.6	-1082.1	-1144.5	-1304.8	-847.8	-870.7	-1236.5	-974.4
Model (3.21)	-986.7	-1000.6	-1024.5	-1089.4	-1168.2	-841.0	-860.8	-1123.5	-946.4
Model (3.22)	-864.4	-884.6	-887.9	-967.5	-1046.2	-743.7	-774.4	-956.2	-819.0
RISK 1									
Model (3.18)	-1035.7	-1040.9	-Inf	-1097.8	-1216.4	-Inf	-Inf	-1165.9	-997.4
Model (3.19)	-988.2	-1004.4	-1017.3	-1057.8	-1144.3	-810.6	-844.4	-1085.4	-948.9
Model (3.20)	-1070.9	-1082.6	-1113.9	-1173.4	-1382.2	-841.3	-Inf	-1276.1	-1014.3
Model (3.21)	-1017.2	-1024.5	-1053.5	-1087.3	-1204.8	-836.9	-Inf	-1146.7	-976.5
Model (3.22)	-872.9	-886.8	-889.9	-960.7	-1048.8	-Inf	-Inf	-955.6	-824.8
RISK 2									
Model (3.18)	-1040.4	-1042.4	-1072.3	-1111.6	-1211.0	-Inf	-Inf	-1176.3	-1001.4
Model (3.19)	-989.7	-1006.0	-1017.6	-1062.8	-1141.4	-816.9	-850.9	-1086.5	-950.0
Model (3.20)	-1093.3	-1097.8	-1133.9	-1206.7	-Inf	-Inf	-Inf	-1305.3	-1036.8
Model (3.21)	-1040.7	-1042.9	-1066.9	-1109.3	-1211.4	-867.1	-Inf	-1170.0	-1001.7
Model (3.22)	-885.8	-897.4	-907.5	-975.1	-1056.1	-758.4	-792.4	-973.0	-838.7
FFR									
Model (3.18)	-1039.4	-1043.3	-1073.1	-1106.4	-1217.4	-Inf	-905.3	-1169.7	-1001.8
Model (3.19)	-989.1	-1006.6	-1019.8	-1060.4	-1144.1	-821.1	-854.7	-1084.4	-950.6
Model (3.20)	-1099.7	-1108.8	-1151.7	-1200.8	-Inf	-894.6	-Inf	-Inf	-1045.8
Model (3.21)	-1036.2	-1042.2	-1070.4	-1102.5	-1216.7	-882.3	-898.5	-Inf	-999.1
Model (3.22)	-881.1	-894.8	-904.2	-971.4	-1054.4	-759.9	-909.8	-970.1	-835.4

Notes: The table shows the Log-Likelihood of the equation set from Chavez-Demoulin, Embrechts and Hofert (2016). The benchmark model based on equation 3.17 is only displayed once, because the Log-Likelihood of it is the same across all covariates. The value "-Inf" indicates the impossibility of fitting the GPD on the tail for a given covariate and model equation.

Similar results can be found for the risk spreads from the bond markets, RISK 1 and RISK 2, with almost identical mean Log-Likelihoods across all models. Consequently, we do not find that the tail risk modeling is dependent on either the spread duration of the term spread or on the minuend of the bond risk spread. Lastly, we observe the same impact of the time factor in our fitted models with debt market covariates as for the equity market specifications. Across the REIT index types, we do not find a clear pattern, as is also the case for the equity market covariates. Instead, the usage types yield unstructured and even puzzling results. The All Equity index, as well as the Residential and Office EREITs, show remarkable reductions in the average Log-Likelihood across models 3.18 to 3.22, whereas the Industrial EREIT and Commercial MREIT time series both perform significantly below average. This heterogeneity is rather weak compared to the equity market covariates, and should thus not be emphasized too heavily.

After having estimated the numerical model fits of the equation set of Chavez-Demoulin, Embrechts and Hofert (2016), we are interested in the model diagnostics for our estimations. We choose the All Equity REIT index and the best performing covariate, the S&P600, to illustrate the diagnostics based on the QQ-Plot of the model residuals, which are asymptotically unit exponentially distributed. We report the theoretical quantiles as well as those of the selected models, including the 95% pointwise asymptotic confidence intervals for the benchmark model (see Figure 4) and in comparison, two selected S&P600 models to illustrate the behavior of the model residual across varying multivariate specifications (see Figure 5).

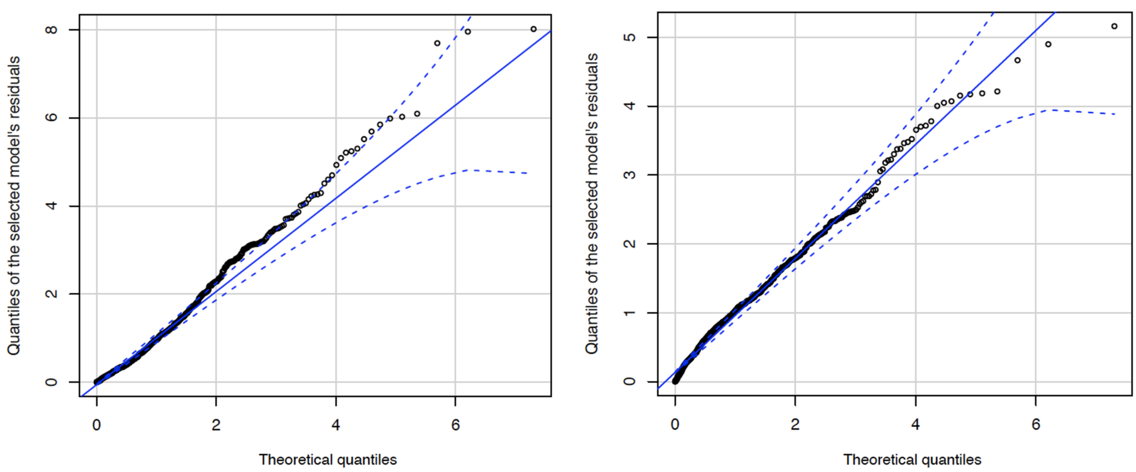
Figure 4: Benchmark model residuals for the All Equity REIT index



Source: Own presentation.

An optical inspection of the benchmark model reveals several insights into the model residuals. For the benchmark model, we find an empirical distribution of the residuals, which is close to the expected unit exponential distribution in the lower part. Nonetheless, we see some structural upper divergence (or left skew) from the theoretical quantiles especially in the center of the plot. This indicates a structurally incorrect modeling of the empirical distribution. The upper divergence of the residuals is also crucial from a risk management point of view, because they reveal structural underestimation of the empirical distribution. This misspecification, derived from the model residuals can be translated directly into a wrong and especially too low risk estimation such as for the VaR. Thus, the benchmark model residuals can be interpreted as a central motivation to re-parameterize the tail risk model. The resulting residuals from the multivariate EVT models show the behavior of the residuals of different specifications. Firstly, we report the residuals of model 3.18, which yields a poorer Log-Likelihood than the benchmark model reported above. For this model, we also find less suitable model residuals, because the upper divergence of the model is even heavier than for the benchmark. Lastly, we report the residuals of model 3.22 in the right part of Figure 5, which shows a clearly improved optical impression of the model residuals, because we do not observe a clear divergence from the theoretical quantiles, especially for the lower part of the distribution. The graphical illustration underlines the favorability of a well-specified multivariate model against the benchmark model. However, the left plot of Figure 5 underlines the need to specify multivariate EVT models with care.

Figure 5: Model residuals for the All Equity REIT index and the S&P600 index as covariate for model 3.18 (left plot) and model 3.22 (right plot)

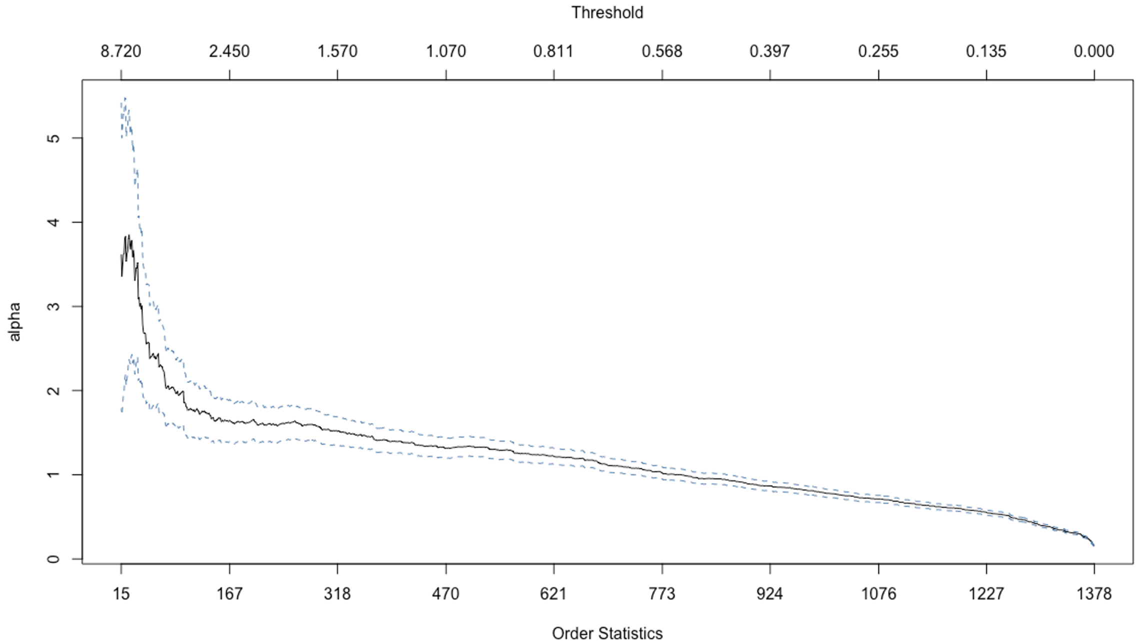


Source: Own presentation.

Lastly as part of the diagnostics, we check for sensitivity to the threshold selection. Typically, EVT models are subject to discussions about user-sided adjustments of the threshold in order to generate favorable results (Karmakar, 2017). Therefore, we use the Hill Plots of the All Equity REIT data to illustrate the sensitivity of the threshold selection (see Figure 6). We exclude the remaining REIT indices from optical analysis, since they yield similar results.

The Hill plot depicts the variation of the parameter as a function of the threshold variation and corresponding number of exceedances, both on the horizontal axis. For our data, we observe the typical volatile impact on the left-hand side of the plot, where little observations fall into the tail, because the threshold is relatively large. Logically, the inclusion of more excesses has a large impact on the parameter. We observe the classic smoothed course of the function with a decreasing number of exceedances, moving from left to right. Most importantly, the estimation should not be based on a threshold which is too large, thus causing the parameter to be located in the left part of the figure (above absolute values for u = 2.450). Since we are using the lowest 25% of the observations, and threshold losses around 0.5 to 0.7 (recalling Table 8), our models are located in the smooth part of the function. Thus, threshold variation in this part of the distribution would not significantly change the model parameters. In sum, we interpret both diagnostics as an empirical legitimation of our multivariate modeling approach.

Figure 6: Hill Plot of the benchmark model for the All Equity REIT Index



Notes: The threshold on the upper x-axis is reported in absolute values. Since we are estimating the lower tail of the distribution, these values represent negative returns (losses). Source: Own presentation.

3.8 Conclusion and further Research

The present study introduces a novel approach to tail risk modeling for REIT returns. We are the first to apply a multivariate EVT regression for the specified type of financial returns to explicitly model the excesses in the tails of the distributions, depending on exogenous covariates. By doing so, we extend the literature of univariate EVT models in the REIT literature, such as Liow (2008), to enhance our understanding of exogenous covariates.

The results reveal several insights into the studied tail modeling of REIT returns. Firstly, the present study is yet another, which underlines the importance of an EVT-based modeling of the tail of REIT returns instead, of the Gaussian normal distribution. Secondly, we address the rarely used lower tail dependence measure as a bivariate assessment metric for the ensuing EVT regression. We find the general usability of the metric, because we observe higher absolute values of lower tail dependence among those covariates, which provide the highest explanatory power to the GPD parameters in the multivariate EVT model. This relationship, however, can only be used as a preliminary analytical step and does explicitly not fully anticipate the relationship or informational power of the covariate in the EVT regression model. The results regarding the accuracy of the multivariate EVT regressions speak strongly for the inclusion of equity market covariates in the specifications. By contrast, exogenous debt market covariates perform significantly worse. We thus advise the application of the former. We find a strong effect of time on the distributional parameters of the REIT return excesses. In addition, we observe strong empirical evidence for the non-linear relationship between time and the GPD parameters, which confirms the application of non-parametric GAMs to allow for greater flexibility.

The results not only enhance our understanding of the employed covariates, which contain information for the tail modeling of REIT return distributions from an academic perspective, but are also of value from a practical point of view. In this context, the enhanced fit of GPDs for the specified tails can be used for risk managers, who are frequently required to estimate risk metrics. We utilized the model residuals to illustrate this issue. Univariate models falsely estimate the risk exposure of REIT positions, as shown by upper divergence of the residuals from theoretical quantiles. The inclusion of exogenous covariates not only improves the model fit by means of the Log-Likelihood, but also by model residuals which are closer to the theoretical quantiles. Further research can address this risk metric estimation, as well as further enhance the modeling of the multivariate EVT approach. Risk metric calculation such as for the VaR or conditional VaR based on the re-parameterized multivariate GPDs, may outperform univariate EVT models like Liow (2008) especially in terms of predictive accuracy of the metrics. Here, back testing studies can provide interesting insights for multivariate models. Additionally, since the present study uses the single covariate testing procedure of Chavez-Demoulin, Embrechts and Hofert (2016), only a limited number of relationships between the GPD parameters and one of the exogenous variables, plus the time component, is studied. Accordingly, further EVT regression modeling of REIT returns that also estimates larger multivariate specifications including multiple covariates, could be fruitful. We see the greatest potential for further research in this field of more complex multivariate models including a larger number of covariates. Lastly, the flexible semi- or non-parametric modeling of the GAM functions could also enable incorporating interaction terms. Thus, the present research article should be interpreted as a starting point for multivariate EVT models of REIT returns.

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3.10 Appendix

Table 11 Bravis Pearson correlation coefficients

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	**All Equity**	1																	
(2)	**Residential**	0.967	1																
(3)	**Office**	0.980	0.940	1															
(4)	**Retail**	0.966	0.910	0.942	1														
(5)	**Industrial**	0.920	0.874	0.904	0.855	1													
(6)	**Mortgage REITs**	0.736	0.709	0.709	0.740	0.630	1												
(7)	**Mortgage Home**	0.696	0.671	0.672	0.702	0.590	0.988	1											
(8)	**Mortgage Commercial**	0.755	0.724	0.735	0.740	0.709	0.796	0.735	1										
(9)	**All REITs**	0.997	0.964	0.977	0.955	0.920	0.753	0.714	0.763	1									
(10)	**S&P500**	0.773	0.715	0.769	0.731	0.737	0.630	0.586	0.676	0.786	1								
(11)	**S&P600**	0.789	0.726	0.787	0.768	0.740	0.660	0.613	0.726	0.794	0.911	1							
(12)	**NASDAQ**	0.687	0.630	0.685	0.643	0.667	0.537	0.496	0.591	0.700	0.942	0.850	1						
(13)	**DJ Industrial**	0.739	0.682	0.734	0.707	0.696	0.620	0.577	0.652	0.751	0.981	0.888	0.903	1					
(14)	**VIX**	-0.6	-0.54	-0.59	-0.55	-0.58	-0.50	-0.47	-0.51	-0.61	-0.83	-0.74	-0.79	-0.81	1				
(15)	**FFR**	-0.01	0.000	-0.01	-0.01	-0.02	0.010	0.009	-0.02	-0.01	0.012	0.005	0.000	0.024	-0.06	1			
(16)	**TERM 1**	0.179	0.159	0.190	0.165	0.196	0.080	0.054	0.166	0.181	0.309	0.308	0.292	0.302	-0.22	-0.06	1		
(17)	**TERM 2**	0.150	0.131	0.167	0.139	0.170	0.046	0.026	0.140	0.150	0.286	0.288	0.271	0.283	-0.21	-0.15	0.843	1	
(18)	**RISK 1**	-0.13	-0.11	-0.14	-0.14	-0.12	-0.16	-0.15	-0.14	-0.13	-0.22	-0.19	-0.2	-0.23	0.189	-0.07	-0.2	-0.22	1
(19)	**RISK 2**	-0.04	-0.03	-0.04	-0.02	-0.05	-0.05	-0.06	-0.03	-0.04	-0.04	-0.02	-0.02	-0.03	0.034	-0.02	-0.04	-0.04	0.28

Source: Own Calculation.

4. Does Retrofitting Pay Off? An Analysis of German Multifamily Building Data

4.1 Abstract

Several studies have investigated the relationship between the energy performance of buildings and housing prices. First, this paper identifies a price premium for energy efficiency within the German rental market. Then, the indexed price differences and associated marginal benefits are compared to the marginal costs of energy retrofits. An extensive database of Germany's largest online platform for housing over a time span from 2016 to 2020 is used in a hedonic regression approach. Additionally, to extract the marginal costs of energy consumption abatement, a dataset of 1,048 rental units regarding green-retrofit measures is utilized. While a significant green premium is identified in the rental market, the findings suggest that it is not high enough to compensate landlords for the money they have to spend to retrofit. The marginal costs exceed the marginal benefits by far. Furthermore, it is found that the German government's recent plans to split the CO_2 tax between landlords and tenants does not change this because the price per metric ton of carbon is insufficiently high. The findings can help both tenants and landlords in their decision-making, as well as policy makers in the implementation of decarbonization efforts.

4.2 Introduction

The most recent Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) made it clear once again that the world's climate is in danger and that drastic steps will be necessary to stem the tide of global warming (Masson-Delmotte et al., 2021). The building sector plays a particularly important role in this scenario. After all, 27% of total global energy-related CO_2 emissions come from the operation of buildings, and a further 10% from the construction industry as of 2020 (United Nations Environment Programme, 2021). In order to achieve the goal of the Paris Agreement (UNFCCC, 2015), to limit the global temperature rise to well below 2 degrees Celsius compared with pre-industrial times (and to make efforts to limit the temperature rise to 1.5 degrees), the European Union (EU) submitted a Nationally Determined Contribution (NDC) which states that the European economy should reach net zero by the year 2050. This goes hand in hand with the widespread decarbonization of the building sector. To meet this challenge, the European Commission presented its strategy for a so-called "Renovation Wave" for climate neutrality and market recovery on October 14^{th} 2020, as part of the European "Green Deal" (European Commission, 2020). Accordingly, the annual building renovation rate is to be at least doubled by 2030. Currently, about 75% of buildings in the EU are not energy efficient, but 85-95% of today's existing buildings will still be in use in 2050. Tools like the Carbon Risk Real Estate Monitor (CR-REM) (see Hirsch, Spanner, & Bienert, 2019), and the wide availability of Energy Performance Certificates (EPCs) have increased both transparency and the ability to identify buildings in need of an energetic update. At the same time, the rate of annual energy renovations in the residential building stock in both Europe and Germany is at only about 1% of the total stock (European Commission, 2019) and remained at this low level quite constantly in recent years. The revised Energy Performance of Buildings Directive (EPBD) mandates that the worst performing 15% of the residential building stock have to be upgraded until 2030 from the current EPC label G to at least label F (European Commission, 2021).

For Germany, the rented residential building stock plays an outstandingly important role for climate impact reduction in comparison to other European countries, as the homeownership rate is below 50% and thus the lowest in the Eurozone, according to data from the Household Finance and Consumption Survey of the European Central Bank and Eurostat (Andrews & Caldera-Sánchez, 2011; Eurostat, 2019). With such a large proportion of rented housing stock, decarbonization of this stock is essential to achieving German carbon reduction targets. In contrast to owner-occupied dwellings, there is a problem with the energy efficient renovation of rented buildings that is frequently mentioned in the literature: The Split Incentive Problem or Landlord-Tenant Dilemma (Schleich & Gruber, 2008). This dilemma is indeed an obstacle to the renovation of many rented buildings. While one party, the landlord, must invest the costs of a retrofit, he cannot benefit directly from the advantages this investment brings. The tenant, on the other hand, benefits directly from the energy renovation, as he faces lower heating costs and enjoys improved thermal comfort after a retrofit. But he, the tenant, has no influence on the investment to achieve energy efficiency. Consequently, from a landlord's perspective, there must be another channel to compensate him for the investment or he would not retrofit his property in the first place. While there are tools that could be used to reduce the split incentive problem, such as green leases that include a cost-benefit sharing mechanism, they require a certain amount of expertise and are not very common in Germany (Cajias, Fuerst, & Bienert, 2019).

At the beginning of 2021, a uniform CO_2 tax was introduced on fuels for heat generation, which is levied on the heating costs. The costs for the CO_2 tax were intended to be shared equally between tenants and landlords, but this ruling was overturned just before it was passed because one of the governing parties at the time voted against it, so that for the time being, 100% of the tax burden is borne by the tenant. Thus, a rent increase remains the most effective way for landlords to recover the investment costs for green retrofits. In this regard, the question of whether higher rents can be achieved by improving the energy efficiency of a property is important for landlords to ask themselves before commissioning any measures (Fuerst, Haddad, & Adan, 2020). In an existing lease contract, the landlord may increase the yearly rent by 8% of the occurring costs, but by a maximum of €3/m², €2 if the previous rent is below €7/m² (§ 559 BGB) after execution of retrofit measures. Modernization also allows for an exception to the rent brake and to generate a premium in the amount under § 559 BGB. Accordingly, the modernization rent increase primarily affects existing contracts while these increases are already reflected in asking rents for new leases. Therefore, an empirical analysis of the rent increase potential through energy modernization is possible and meaningful based on asking rents. Another aspect that could increase the benefit of lower energy consumption of an apartment in the future from the landlord's perspective are tax savings. This is the case because the new German government that is made up of three parties, namely Social Democrats (SPD), Green party (BÜNDNIS90/Die Grünen) and Liberals (FDP) recently announced that the carbon tax burden will be split between landlords and tenants (SPD, BÜNDNIS90/Die Grünen, & FDP, 2021).

This paper analyses how energy performance is transferred to the rent of an apartment or a house and tests how and if green premia are present. To do so, an extensive dataset of rental listings in Germany is examined, wherein the energetic conditions from Energy Performance Certificates (EPCs) are utilized as central exogenic variables. This is possible, since the EU EPBD obliges member states to adopt an energy efficiency certification scheme which ensures that a dwelling has an independent rating of its energy performances when offered for rental (EUR-Lex, 2018). In addition, a dataset with information on retrofits of multi-family houses in Germany is used to compute marginal costs for energetic improvements in the context of building renovation. The central research question of the present study is threefold. The first part explores the question of whether, in the German market for rented apartments in multi-family buildings, there is a price premium for energy efficiency (green premium). Provided that a price premium is indeed found, the subsequent research-focus is on whether the rent increase potential from an improvement in energy efficiency is sufficient to offset the costs of a retrofit, over the expected useful life of the asset. If this is rejected, it is necessary to investigate whether the regulatory framework that is currently in place in Germany provides sufficient incentives for the implementation of energy efficiency measures. In this respect, it will be examined whether the current level and design of the CO_2 tax on fossil fuels for residential heating in Germany provides a sufficiently strong incentive for owners of energetically poor multi-family houses to retrofit their properties for energy efficiency.

The paper is organized as follows. Section 4.3 introduces the theoretical background and reviews literature on the topic. In Section 4.4, the two datasets are described, whereas in Section 4.5, the methodology of both the statistical model estimation and derivation of marginal benefit and marginal cost curves is presented. The results of the hedonic pricing model, as well as the derived curves, are placed in relation to each other and supplemented by the influence of the assumed future course of the

CO_2 taxation in Section 4.6. Lastly, Section 4.7 concludes the paper.

4.3 Literature Review

In the field of research on the influence of energy efficiency on the price of buildings and the achievable rents, a multitude of studies have emerged which can generally be divided into two main strands. One refers to green labels which are based on certain characteristics, and the other focuses on absolute energy consumption to proxy for energy efficiency. Early examples of both date back to the eighties (Johnson & Kaserman, 1983; Gilmer, 1989). Since then, the price effect of green labels in commercial real estate has been investigated in many studies (Wiley, Benefield, & Johnson, 2010; Kok, Miller, & Morris, 2012; Fuerst & McAllister, 2011; Simons, Robinson, & Lee, 2014; Robinson & McAllister, 2015; Addae-Dapaah & Wilkinson, 2020). Also, mostly during the last decade, in an extensive body of literature, EPCs which provide information about the energy performance of buildings, have been utilized to implement energy efficiency in hedonic modeling, and test its price effect. The first to demonstrate that higher energy efficiency, as measured by EPC ratings, is capitalized into purchase prices, were Kok & Brounen (2011) who studied transactions of about 32,000 residential properties that occurred between 2008 and 2009 in the Netherlands. They found that properties with a green label rated A, B or C had a premium of 10%, 5.5% and 2.2%, respectively, relative to properties rated D.[1] In subsequent studies, this fundamental relationship of a significant price premium for green buildings has been confirmed several times for different housing markets, but with varying premium levels (Cajias & Piazolo, 2013; Kholodilin & Michelsen, 2014; Fuerst, McAllister, Nanda, & Wyatt, 2016; Dell'Anna, Bravi, Marmolejo-Duarte, Bottero, & Chen, 2019; Taltavull de La Paz, Perez-Sanchez, Mora-Garcia, & Perez-Sanchez, 2019; Copiello & Donati, 2021; Cadena & Thomson, 2021). A few studies, however, indicate that there is no significant, a negligibly small or even a negative relationship. The findings of Cerin, Hassel & Semenova (2014), for example, suggest that energy efficiency causes a price premium only for certain age and property-price classes in the Swedish residential market. Interestingly, Yoshida & Sugiura (2010) identified a price discount in the Tokyo market for newly constructed green condominiums of 5.5%, while green condominiums on average are traded at a premium. Also, meta-analyses, such as that of Cespedes-Lopez, Mora-Garcia, Perez-Sanchez & Perez-Sanchez (2019), have emphasized that the effects are not unambiguous and their strength depends strongly on the way the EPC rating is included in the analysis and on the region considered. By meta-regression they aggregated the results of 66 prior studies and find that EPCs entail an overall price premium of 4.2%. However, this varies when broken down by continent. Average premiums of 5.36% are observed in North America, 4.8% in Asia, and the lowest in Europe, on average 2.3%. Similarly, Wilkinson & Sayce (2020) in another meta-analysis examined, in a European context, the relationship between EPCs and capital (or rental) values. They once more verify that the majority of research shows there is a positive re-

[1] Note that EPC classes are not defined in the same way in all jurisdictions, but differ both in terms of their number and the respective range of values. For example, the EU defines classes A to G while Germany is using a differentiation of A+ to H.

lationship between observed market price and energetic performance, but also that EPC ratings are not a strong value driver compared to other variables. In addition, they also confirm that energy upgrades can increase value, but point out that this does not go so far that the costs outweigh the increase in value. By contrast, Copiello & Donati (2021) conclude that investing in building energy efficiency can be economically viable up to a certain extent, when comparing the marginal benefit of a retrofit, and hence the green premium, with the marginal cost to save one kilowatt hour (kWh), based on housing price data for the town of Padua in Italy. Specifically, they point out that housing in the worst energy rating bands can be profitably, meaning that marginal benefit exceeds marginal costs, refurbished up to an energy performance index of about 50 kWh/m^{2}a to 40 kWh/m^{2}a, depending on whether or not tax incentives are provided. It is important to note that this finding is based on substantial premiums of up to 61.7% from the lowest to the best EPC rating bands, the latter being decisive for further analysis.

Most of the aforementioned studies have focused primarily on purchase transactions and one cannot assume that the energy efficiency effects identified on the residential sales market can be simply applied to the rental market, as these markets differ both in the degree of formalization of disclosure of rights (e.g. involvement of real estate agents and notaries) and in the prevalence of compliance controls (Dressler & Cornago, 2017). However, the influence of EPC ratings has also been investigated, albeit to a lesser extent, in the context of rental apartments: Cajias & Piazolo (2013) identify a green premium in the German rental market for the energy classes “B”, “C” and “D” of 13.3% (which is on average €0.47/m^2), 13.5% (€0.59/m^2) and 16.3% (€0.74/m^2) higher rent as the reference class, the lowest energy efficient. Hyland, Lyons & Lyons (2013) find a significant lower premium for rental apartments than for property sales. Their research, for which they used rental advertisement data from Ireland, also suggests a significantly lower premium than that found by Cajias & Piazolo (2013). For A-rated dwellings, Hyland, Lyons & Lyons (2013) find a gain of 1.8% green premium relative to otherwise similar D rated dwellings. Dressler & Cornago (2017) find, with data for rentals in the city of Brussels, that highly energy-efficient dwellings are associated with a 4.8% rent premium when compared to low-energy-efficient dwellings, which amounts to €50 per month for the average apartment in their dataset, which has 107 m^2 of living space. Additionally, they point out that disclosing energy-efficiency information for dwellings with intermediate energy-efficiency results in a discount, which they interpret as a strategic motivation not to disclose a dwelling’s energy performance when it is not in the top classes. Cajias, Fuerst & Bienert (2019) with a big dataset of nearly 760 thousand observations across over 400 local markets in Germany, estimated that rents for A+, A, B and C-rated rental apartments are on average 0.9%, 1.4%, 0.1% and 0.2% higher than the reference category D, whereas dwellings in the categories below E, F, G and H are subject to rent discounts of up to -0.5%. By analyzing different subsamples, Cajias, Fuerst & Bienert (2019) also demonstrate that the Top 7 real estate markets, i.e. Berlin, Hamburg, Munich, Frankfurt, Cologne, Düsseldorf and Stuttgart, show less sensitivity to energy-efficiency, while in secondary markets, the premium is enhanced by up to 1.4% points (for A+), while discounts are also increased by up to 1.8% points. Additionally, the premiums for the A category increased over time from 0% in 2013 to 1.4% in 2017 and the brown discounts for G and H-rated apartments decreased over time. Furthermore, and in line with Fuerst, Haddad & Adan (2020), evidence for a negative coherence of time on the market and energy-efficiency of rental units is provided. In a more recent published scientific work for Germany, some of the earlier findings were confirmed by Pommeranz & Steininger (2021), who once more demonstrate that rents are on average lower for apartments with higher energy consumption. Furthermore, they suggest that in neighborhoods with higher green awareness and higher purchasing power, lower rents for energy-inefficient apartments are payed, while the effects of purchasing power are higher than for green awareness.

Overall, the majority of studies suggest that a green premium also exists in the rental market, but that the level of this premium differs according to various factors. This present paper is part of the existing debate and aims to broaden it by comparing the efficiency gains from a retrofit with the associated marginal costs, and analyzing whether the monetary benefits justify the implementation of retrofit measures from the landlord perspective.

4.4 Data

4.4.1 Data on asking rents

The original dataset comprises more than 2 million observations of rental listings from the leading online platform in Germany for housing, ImmobilienScout24, for the time span 2016 to year 2020 and in cities with a population of more than 100,000. Data access was provided by the Research Data Centre Ruhr at the RWI – Leibniz-Institute for Economic Research (FDZ Ruhr). The dataset is identified at DOI: "10.7807/immo:red:hm:suf:v3".

Since it is not transaction data or data from rent agreements, but from offerings on an online platform, the information was entered by the platform users, which means that it is subject to data entry bias. To deal with this issue, we cleared the data of implausible values such as zero or negative area, and of missing values that are required for the estimation such as energy demand per square meter. After data-clearing processes, we are left with 533,780 observations with full hedonic characteristics. The dataset contains information on rent, apartment size, energy demand per square meter, number of rooms, quality and if the features Elevator, Balcony, Guest WC, Built-in Kitchen, Garden and Cellar are applicable. The categorial variable for quality has the classifications simple, normal, sophisticated and luxury, which we include as binary variables as well as for the aforementioned equipment features. We also add two socioeconomic variables to the dataset by including the number of households in a city and the average household income. The socioeconomic data was retrieved from GfK (http://www.gfk.com). Table 12 depicts the descriptive statistics. The average rent for a unit is at €751.86, the average rent per square meter is €10.89 and the average energy demand per square meter is at 118 kWh/m^{2}a, which equals EPC D. The average apartment age is 45 years, whereby the age of the building is calculated as the difference between the year of construction and the year in which the rental listing was placed. About 1.6% of the properties are classified as simple, 49.6% as normal, 43.4% as sophisticated, and only 0.5% as luxury. Additionally, Table 13 depicts the corresponding Pearson correlation coefficients.

Table 12 Descriptive statistics

Variable	Unit	Mean	Std. Dev	Min.	Q5%	Q30%	Median	Q70%	Q90%	Max.
Asking rent	€ per month	751.864	529.959	101.5	269	435	599	849	1380	12000
Log asking rent	Log € p.m.	6.441	0.583	4.62	5.595	6.075	6.395	6.744	7.23	9.393
Rent per m^2	€/m^2 p.m.	10.188	4.412	0.988	5.102	7.375	9.375	11.54	15.833	83.673
Energy consumption	kWh/m^2 p.a.	118.394	54.088	1.1	42	87	114.5	141.37	186.7	499.21
Log energy consumption	Log kWh/m^2 p.a.	4.655	0.525	0.095	3.738	4.466	4.741	4.951	5.23	6.213
Constructed	Number	1972.583	32.725	1901	1910	1958	1972	1995	2016	2020
Age	Number	45.014	32.703	0	0	22	46	60	99	119
Living Area	m^2	72.711	31.382	10.1	32	56	67.39	81.6	111	482
Floor	Number	2.185	1.825	-1	0	1	2	3	4	45
Rooms	Number	2.53	0.953	1	1	2	2.5	3	4	10
Households	Number	530232.9	632779.6	50781	62580	137849	303140	396228	2008823	2008823
Purchasing Power	€/household p.a.	41783.01	5714.261	31415.1	34586.63	37335.6	41418.41	45003.1	48007.09	54784.02
Elevator	Binary 1 = yes	0.358	0.48	0	0	0	0	1	1	1
Balcony	Binary 1 = yes	0.715	0.451	0	0	1	1	1	1	1
Guests WC	Binary 1 = yes	0.207	0.405	0	0	0	0	0	1	1
Built-in Kitchen	Binary 1 = yes	0.448	0.497	0	0	0	0	1	1	1
Garden	Binary 1 = yes	0.195	0.396	0	0	0	0	0	1	1
Cellar	Binary 1 = yes	0.792	0.406	0	0	1	1	1	1	1
Simple equipment	Binary 1 = yes	0.016	0.124	0	0	0	0	0	0	1
Normal equipment	Binary 1 = yes	0.496	0.5	0	0	0	0	1	1	1
Sophisticated equipment	Binary 1 = yes	0.434	0.496	0	0	0	0	1	1	1
Luxury equipment	Binary 1 = yes	0.054	0.225	0	0	0	0	0	0	1

Source: Own Calculation.

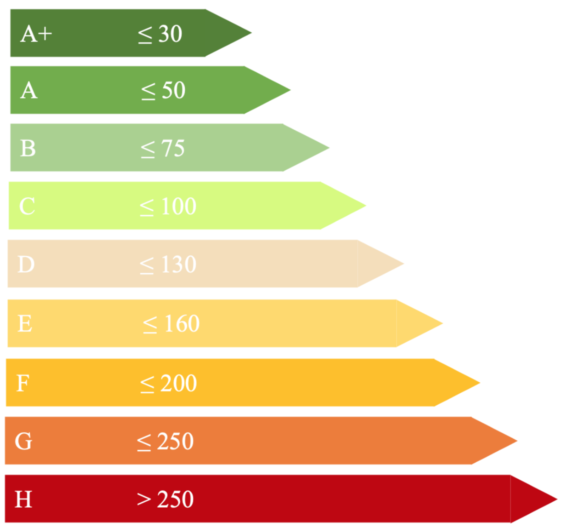
Table 13 Pearson correlation matrix of variables

	Variable	i	ii	iii	iv	v	vi	vii	viii	ix	x	xi
i	Asking rent	1										
ii	Log asking rent	0.91	1									
iii	Rent per m^2	0.62	0.65	1								
iv	Energy consumption	-0.26	-0.28	-0.26	1							
v	Log energy consumption	-0.30	-0.33	-0.30	0.93	1						
vi	Constructed	0.27	0.30	0.30	-0.46	-0.51	1					
vii	Age	-0.27	-0.30	-0.30	0.46	0.51	-1.00	1				
viii	Living Area	0.77	0.75	0.08	-0.15	-0.18	0.13	-0.13	1			
ix	Floor number	0.11	0.08	0.11	-0.05	-0.03	0.03	-0.03	0.04	1		
x	Number of Rooms	0.51	0.54	-0.08	-0.07	-0.08	0.04	-0.04	0.80	0.00	1	
xi	Households	0.27	0.30	0.32	-0.04	-0.03	-0.06	0.05	0.10	0.10	-0.01	1
xii	Purchasing Power	0.29	0.35	0.46	-0.04	-0.07	0.21	-0.20	0.06	-0.02	0.01	-0.24
xiii	Elevator	0.33	0.34	0.37	-0.36	-0.39	0.46	-0.46	0.16	0.26	0.01	0.13
xiv	Balcony	0.27	0.34	0.13	-0.20	-0.21	0.30	-0.30	0.29	0.01	0.23	0.08
xv	Guests WC	0.49	0.50	0.17	-0.17	-0.20	0.23	-0.23	0.55	0.02	0.44	0.02
xvi	Built-in Kitchen	0.27	0.30	0.43	-0.12	-0.12	0.18	-0.17	0.04	0.05	-0.08	0.20
xvii	Garden	0.03	0.03	-0.02	-0.01	-0.02	-0.01	0.01	0.06	-0.16	0.08	-0.04
xviii	Cellar	0.06	0.08	-0.05	-0.06	-0.05	0.09	-0.09	0.11	-0.06	0.15	-0.13
xix	Simple equipment	-0.08	-0.10	-0.08	0.06	0.06	-0.06	0.06	-0.05	0.01	-0.02	-0.01
xx	Normal equipment	-0.45	-0.51	-0.43	0.28	0.32	-0.29	0.29	-0.30	-0.01	-0.15	-0.11
xxi	Sophisticated equipment	0.29	0.39	0.32	-0.22	-0.25	0.22	-0.22	0.19	-0.01	0.10	0.08
xxii	Luxury equipment	0.41	0.34	0.29	-0.17	-0.20	0.17	-0.17	0.27	0.04	0.13	0.08
	Variable	**xii**	**xiii**	**xiv**	**xv**	**xvi**	**xvii**	**xviii**	**xix**	**xx**	**xxi**	**xxii**
xii	Purchasing Power	1										
xiii	Elevator	0.11	1									
xiv	Balcony	0.10	0.23	1								
xv	Guests WC	0.13	0.20	0.22	1							
xvi	Built-in Kitchen	0.13	0.19	0.08	0.10	1						
xvii	Garden	-0.02	-0.07	0.00	0.06	0.03	1					
xviii	Cellar	0.09	0.03	0.16	0.11	-0.02	0.10	1				
xix	Simple equipment	-0.01	-0.04	-0.04	-0.05	-0.07	-0.03	-0.03	1			
xx	Normal equipment	-0.19	-0.28	-0.21	-0.28	-0.25	-0.05	-0.05	-0.13	1		
xxi	Sophisticated equipment	0.16	0.21	0.18	0.20	0.21	0.04	0.04	-0.11	-0.87	1	
xxii	Luxury equipment	0.08	0.18	0.09	0.21	0.14	0.04	0.03	-0.03	-0.24	-0.21	1

Source: Own Calculation.

As indicated in Table 13, the energy consumption and age have a clearly positive correlation, which has resulted from the tightening of energy consumption regulations for new construction over the course of time (Fuerst, McAllister, Nanda & Wyatt, 2016). One indicator for an expected green premium is that energy consumption and rent per square meter have a negative correlation. In order to examine the relationship between energy demand and rental potential, the energy efficiency ratings, which are also called EPC bands or EPC classes, are used in addition to the absolute value per square meter. The EPC classes are not included in the data from the outset, but are calculated on the basis of the energy demand values according to German legislation. Figure 7 shows the EPC rating bands from H (the worst) to A+ (the best) like they are defined in the German Building Energy Act (GEG). For example, for a building to be assigned to energy efficiency class A, its annual energy demand in kilowatt-hours per square meter per year (kWh/m^{2}a) has to be in the range between 31 and 50 kWh/m^{2}a.

Figure 7: German energy efficiency classes of residential buildings according to German Building Energy Act



Source: Own depicition

Accordingly, we construct a binary variable for each EPC-rating band. The summary statistics for the EPC-variables generated in this way can be found in Table 14.

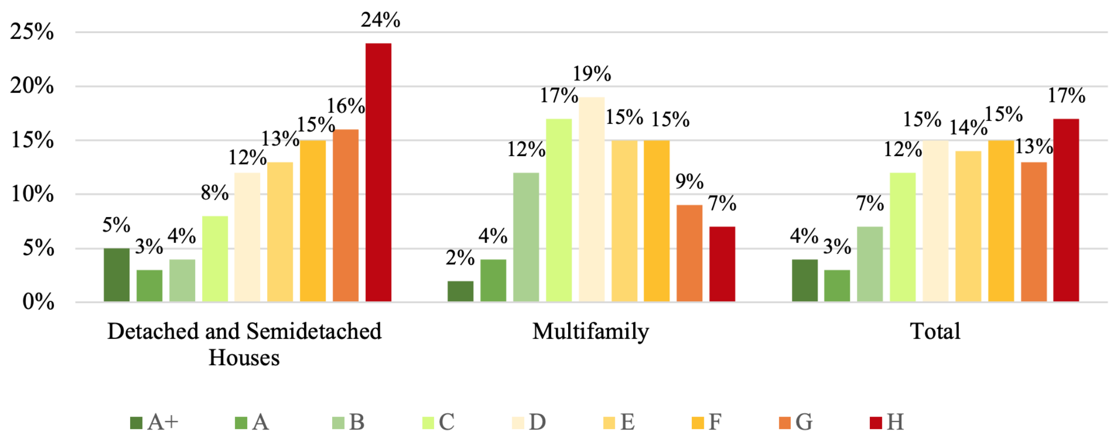
Table 14 Summary statistics and Pearson correlation coefficients for EPC classes

	Variable	**Mean**	**Mean energy kWh/m²a**	**Mean rent €/m² p.m.**	**i**	**ii**	**iii**	**iv**	**v**	**vi**	**vii**	**viii**	**ix**	**x**
i	Rent (€/m^2)	10.19			1									
ii	Energy (kWh/m^2a)	118.39			-0.26	1								
iii	EPC – A+	0.02	19.2	13.18	0.11	-0.29	1							
iv	EPC – A	0.05	40.9	13.78	0.19	-0.34	-0.04	1						
v	EPC – B	0.15	62.2	12.57	0.23	-0.43	-0.07	-0.1	1					
vi	EPC – C	0.16	87.4	9.83	-0.04	-0.25	-0.07	-0.1	-0.19	1				
vii	EPC – D	0.23	114.7	9.27	-0.11	-0.03	-0.09	-0.13	-0.23	-0.24	1			
viii	EPC – E	0.18	143.5	9.34	-0.09	0.22	-0.07	-0.11	-0.2	-0.21	-0.26	1		
ix	EPC – F	0.13	176.6	9.27	-0.08	0.41	-0.06	-0.09	-0.16	-0.17	-0.21	-0.18	1	
x	EPC – G	0.05	219.2	9.19	-0.05	0.43	-0.04	-0.05	-0.1	-0.1	-0.13	-0.11	-0.09	1
xi	EPC – H	0.02	287.7	8.82	-0.04	0.45	-0.02	-0.03	-0.06	-0.06	-0.08	-0.07	-0.05	-0.03

Source: Own Calculation.

As can be seen from Table 14, most apartments are in EPC class D (24%), followed by E (18%) and C (16%) but only very small proportions of the buildings are assigned to the very upper and very lower rating bands. While the shares of the classes A+ and A are close to the share in the German building stock at 2% (A+) and 5% (A), the very lowest groups G and H are massively underrepresented. In the multi-family housing stock in Germany, their shares are around 7% (H) and 9% (G) as depicted in Figure 8 while in the data sample, they comprise only 2% (H) or 5% (G). A possible reason for this low percentage of the lower rating bands in the data may be that owners who advertise these apartments for rent are aware that mediocre and low energy efficiency potentially reduces the rentability or results in a price discount, and therefore do not include energy performance in the advertisement (Dressler, & Cornago, 2017).[2]

Figure 8: Frequency distribution of building efficiency classes according to the final energy demand in the German building stock



Source: Own depiction according to BMWi (2020).

Table 14 also shows the mean energy consumption in kWh/m^{2}a and mean rent for each EPC rating band. The highest average rent is charged in class A (€13.78/m^2 p.m.), while the lowest is charged in class H (€8.82/m^2 p.m.). The rent differential is not constant, for example, the average monthly rent per square meter in energy efficiency class E with €9.34/m^2 is slightly higher than in class D with €9.27/m^2. Rent and energy consumption show a negative correlation coefficient of -0.26 while the correlation coefficients of the different EPC classes and the rent per square meter have changing signs. For classes A+ to C the sign is positive and from class D downwards it is negative. The range of correlations is between 0.23 and -0.09. Surprisingly, the highest or lowest correlations are not at the extreme points of the energy-efficiency classes, i.e. at A+ and H, but at B and D. Due to the correlations one would expect the presence of a green premium in the classes A+ to C.

[2] According to German law, an apartment may be advertised with the inclusion of the EPC whereas it is mandatory to present the EPC to the prospective tenant at the latest at the time of the apartment tour.

4.4.2 Green retrofit data

The data used for this study regarding the cost of green retrofits and corresponding efficiency gains was collected by the General Association of the German Housing Industry (Bundesverband deutscher Wohnungs- und Immobilienunternehmen e. V.; GdW) and some of its partner companies and kindly made available to us. The sample comprises exclusively multifamily buildings in Germany and includes observations on 1,048 residential units in 27 properties with a total of 64,519 m^2 of living space before and after retrofit measures. The data contains a description of the measures carried out, the year of the retrofit, renovation costs, the energy demand before and after refurbishment, and the energy consumption before and after refurbishment, whereas energy demand and consumption are included in relation to the living space. The term energy demand refers the amount of energy per square meter that is required to provide heat to the unit. It is calculated on the basis of normative standard conditions which are defined in the GEG. The energy consumption, on the other hand, is based on values actually measured over a 3-year period, before and after each retrofit, and in the dataset are only adjusted for temperature differences. Since the EPC classes according to the GEG do not refer to the living space but to the usable space, the energy consumption and demand must be converted to this. Here, we apply the simplified conversion according to GEG § 82 para. 2, which for this purpose specifies a conversion factor of 1.2 for multi-family houses.

Additionally, because the year in which the retrofit measures were carried out varies, we extrapolate, or in the case of one observation for which the retrofit took place in 2019, we discount the costs of the retrofit to 2018, using the construction cost index for Germany provided by the German statistical office (Destatis, 2022a) in order to make them comparable. We choose 2018, as this is the average year of the offering data with which the retrofit costs are compared later. Table 15 shows descriptive statistics of the data sample. In terms of energy demand, the average value before retrofit is 236.88 kWh/m^2a and 69.97 kWh/m^2a afterwards. This corresponds on average to a retrofit starting from EPC class G and resulting in EPC class B. In terms of actual measured consumption, on average a refurbishment performance of 176.28 kWh/m^2a to 94.39 kWh/m^2a is realized, i.e. EPC band G to D. The average absolute energy saving in the energy demand is 166.91 kWh/m^2a, while the actually measured saving is less than half as high at about 81.89 kWh/m^2a.

Table 16 shows the Pearson correlation coefficients for the retrofit data. It can be noted here that the cost of retrofit per square meter correlates negatively with both the number of housing units and the total usable space in the building, implying that the average cost of retrofit decreases with the size of the building and that economies of scale may be achieved accordingly. However, the positive correlation coefficients of the costs with the initial state before renovation in kWh/m^2a and the additional state afterwards are particularly noteworthy. This indicates rising marginal costs of retrofitting with increasing energetic performance.

Table 15 Descriptive statistics for green retrofit data

Variable	**Mean**	**S**	**Min.**	**Q25**	**Median**	**Q75**	**Max.**
Number of units	39	26	6	24	29	47	114
Total living area (m^2)	2389.57	1662.66	378.42	1310.60	1927.10	2983.61	7725.66
Year of retrofit	2016.48	1.72	2013.00	2015.00	2017.00	2018.00	2019.00
Cost of retrofit (EUR/m^2)	828.02	312.30	200.52	594.04	787.53	1104.19	1344.84
Energy demand before retrofit (kWh/m^2a)	236.88	77.00	124.97	166.31	249.00	291.05	387.40
Energy demand after retrofit (kWh/m^2a)	69.97	25.47	33.58	50.06	74.00	84.41	118.49
Energy consumption before retrofit (kWh/m^2a)	176.28	39.26	114.48	150.99	181.24	194.05	258.30
Energy consumption after retrofit (kWh/m^2a)	94.39	20.11	57.18	83.46	91.75	98.85	151.37
Energy demand saving (kWh/m^2a)	166.91	62.72	79.98	113.52	179.00	204.10	322.40
Energy consumption saving (kWh/m^2a)	81.89	35.85	25.44	53.47	89.16	101.97	173.33

Source: Own Calculation.

Table 16 Pearson correlation coefficients for green retrofit data

	Variable	**i**	**ii**	**iii**	**iv**	**v**	**vi**	**vii**	**viii**	**ix**
i	Number of units	1								
ii	Total living area (m^2)	0.95	1							
iii	Year of retrofit	-0.12	-0.02	1						
iv	Cost of retrofit (€/m^2)	-0.32	-0.30	-0.16	1					
v	Energy demand before retrofit (kWh/m^2a)	-0.34	-0.35	-0.33	0.12	1				
vi	Energy demand after retrofit (kWh/m^2a)	-0.38	-0.36	-0.10	-0.20	0.64	1			
vii	Energy consumption before retrofit (kWh/m^2a)	-0.19	-0.15	-0.12	0.34	0.72	0.37	1		
viii	Energy consumption after retrofit (kWh/m^2a)	-0.17	-0.25	0.26	-0.24	0.27	0.42	0.42	1	
ix	Energy demand saving (kWh/m^2a)	-0.26	-0.28	-0.36	0.23	0.95	0.37	0.72	0.15	1
x	Energy consumption saving (kWh/m^2a)	-0.12	-0.02	-0.28	0.50	0.64	0.17	0.86	-0.10	0.70

Source: Own Calculation.

4.5 Methods

4.5.1 Hedonic Pricing and Generalized Additive Model

The econometric approach to analysing whether higher or lower energy consumption in rental multifamily housing is associated with a significant price premium involves two steps. Our first step is to estimate a hedonic pricing model (HPM), as empirically justified by Sirmans, MacPherson & Zietz (2005), which is the standard methodology for examining value determinants in housing. The baseline model is specified as follows:

$$Y = X\beta + f(x_i) \tag{4.1}$$

With apartment unit factors (i), energy consumption $[EC]$ proxies (j), socioeconomic indicators (k), binary locational variables $[L]$ on ZIP code level (l) and binary time dummy controls $[K]$ by listing year (t):

$$\log(price/m^2)_i = \beta X_i + \mu EC_j + \delta S_k + \theta L_l + \lambda K_t + \varepsilon_i \tag{4.2}$$

In doing so, we apply the ordinary least squares estimation method on the fully linear form and thus use the log of price per square meter as the response variable, and the log of energy consumption per square meter as the energy proxy. Some studies argue that the standard HPM approach overestimates the influence of energy consumption and that using different alternatives such as including spatial dependencies (e.g. Conway et al., 2010; Bisello, Antoniucci, & Marella, 2020; Copiello & Donati, 2021;) or applying nonlinear estimation techniques like Generalized Additive Models (GAM) (Cajias & Ertl, 2018; Cajias, 2018), produces better results than the standard approach. Spatial models could not be applied in the present study, as the dataset was cleared from addresses or granular location information by the provider for privacy reasons. Accordingly, in a second step to apply a GAM approach, we use partial residual plots on our HPM estimates to identify possible nonlinear relationships between predictor and response variables (Brunauer, Lang, Wechselberger, & Bienert, 2010). A visual inspection reveals that all non-categorial covariates suggest nonlinear modeling to some degree, namely the unit area, building age, floor number, energy consumption per square meter and the socioeconomic variables of purchasing power and number of households. Consequently, these are modeled non-linearly within an additive mixed approach with mixed covariates of parametric estimates and nonlinear functions. We estimated four different model specifications of which two are solely linear. Two more are mixed with both linear and nonlinear covariates, whereas non-linearity is accounted for by modeling the nonlinear covariates with penalized splines. For each HPM and by means of the GAM approach, a further model is estimated in which the energy consumption is represented by the EPC rating bands. Since we are interested in the rent difference of the better classes compared to the worst performing buildings, we set the classes G and H as the reference category. Due to the negative correlation between energy consumption and price per square meter, this approach leads to the expectation that the regression coefficients of the binary variables for the classes A+ to F have a positive sign, and that an increase in the strength of the effect can be observed with increasing energy efficiency.

4.5.2 Marginal Benefit and Marginal Cost Curves

In environmental economics, the concept of marginal abatement costs (MAC) is used together with marginal benefit (MB) to determine the optimal pollution-reduction level (Eory, Topp, & Moran, 2013). MAC are defined as necessary costs per additional unit of emissions reduction, and MB as the financial benefit resulting from the avoidance of this unit (McKitrick, 1999). The economically optimal level of abatement is located where MAC are equal to the resulting MB (Pearce & Turner, 1990). As already indicated, the term MAC is most often used in the academic literature in relation to pollution or greenhouse gas emissions. Since, in the present study, our analysis is not based on avoided emissions, but on energy savings, the term marginal cost (MC) is more appropriate and will be used in the following analysis, although the concept is very similar.

Following Copiello & Donati (2021), MB for energetic improvements in buildings can be calculated as follows:

$$MB = \Delta TB / \Delta Epi \tag{4.3}$$

where ΔTB is the change in total benefit (TB), and hence, the price premium due to an increase in energy efficiency after a green retrofit. And ΔEpi is the change in the energy performance index Epi which is measured in kWh/m^{2}a. To apply this calculation procedure to the coefficients resulting from the estimation of the HPM for each energy efficiency class and then estimate a marginal benefit curve (MBC), we use the average savings between two classes resulting from the data set, and the associated rent premium at the point of means for the reference category (EPC G & H).

Analogous to the calculation of the MB, the marginal costs can be calculated as the quotient of total costs (ΔTC) per square meter to undertake the green retrofit measures and the resulting change in the energy performance index (ΔEpi):

$$MC = \Delta TC / \Delta Epi \tag{4.4}$$

To derive the appropriate slope of the marginal cost curve, we relate the MC determined for each observation i to the respective intervention level IL_i which is defined as average of energy performance index before (Epi_i^b) and energy performance index after (Epi_i^a) retrofit:

$$IL_i = \frac{Epi_i^b + Epi_i^a}{2} \tag{4.5}$$

In order to make the curve determined, that is shifted towards a lower degree of energy efficiency comparable with the MBC, it has to be shifted back toward a higher level of energy efficiency by factor S. S being defined as:

$$S = \left(\frac{1}{n}\sum_{1}^{n} Epi_i\right)\frac{1}{2} \tag{4.6}$$

The two curves derived in this way can be used to graphically analyze the extent to which the implementation of the measures pays off economically in terms of an increase in rents, provided there is an intersection of the curves. The intersection of the MBC and MCC indicates the optimal level of energy reduction.

4.6 Results and Implications

The following presentation of results consists of three parts. We first estimate the price impact of energy efficiency ratings and then proceed to apply the methodology described above to determine the MBC, which we subsequently compare with the MCC in order to assess the profitability of retrofit measures. As a final subsection, we address some caveats with regard to the interpretation of the results.

4.6.1 Hedonic Pricing Model regression results

Table 17 shows the regression results for energy-related variables of four hedonic model specifications that were estimated with the natural logarithm of asking rents in Euros per month, as the response variable. Included are energy performance indicators, hedonic and socioeconomic covariates with 533,780 observations from 2016-Q1 to 2020-Q4. Full regression results with coefficients for all included covariates can be found in the appendix of this chapter in Table 19. Model (1), is the standard linear model with the numeric energy index parameter log(energy/m^2) as exogenic variable, model (2) is the otherwise similar OLS model but with energy efficiency bands as exogenic variables, while model (3) is the counterpart to (1), but estimated in a GAM framework and likewise (4) showing the corresponding GAM model estimates to model (2) with EPC rating bands. Spatial fixed effects on ZIP code level and year time dummies have been included in all model estimations.

For all estimates, a significant influence of the energy quality of the buildings on the rent was found, confirming the results of previous studies. As expected, the positive impact of really high energy quality is much greater than for slightly better apartments according to the results of the linear regression. Surprisingly, the signs of the small but significant coefficients for EPC classes D, E and F in model (2) are negative. However, this result in the linear regression appears plausible when the correlation coefficients of the EPC classes with the rent per square meter from Table 16 are recalled, because the negative correlation for the classes G and H is weaker than for E, F, and G. This relationship, which is difficult to explain economically, is not found in the analogous GAM model (4), which suggests that the non-linear inclusion of several variables has improved the model estimation. This is also supported by the higher adjusted R^2.

Table 17 Regression results for energy-related exogenic variables

log(price/m²)	**(1)**	**(2)**	**(3)**	**(4)**
Method	OLS	OLS	GAM	GAM
log(energy per m²)	-0.058***		8.047***	
	(0.001)		(edf)	
A+		0.134***		0.039***
		(0.002)		(0.002)
A		0.109***		0.024***
		(0.001)		(0.001)
B		0.069***		0.021***
		(0.001)		(0.001)
C		0.009***		0.008***
		(0.001)		(0.001)
D		-0.002**		0.003***
		(0.001)		(0.001)
E		-0.003***		0.001
		(0.001)		(0.001)
F		-0.002**		0.002*
		(0.001)		(0.001)
Spatial FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	533,780	533,780	533,780	533,780
Adjusted R^2	0.926	0.927	0.934	0.934

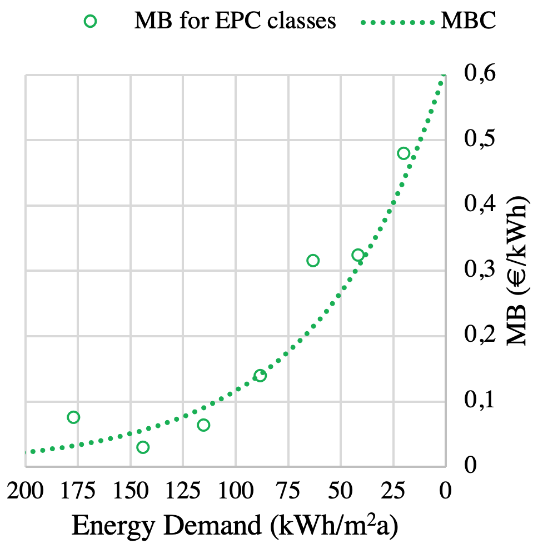
*Notes: Significant at *10, **5 and ***1% levels; standard errors in brackets below the estimated coefficient. edfs are reported for nonlinear estimates within nonlinear models. The estimated coefficients are marked with "edf" in brackets below. The reported significance shows the significance of smooth terms.*

From the estimated coefficients of binary variables in a semi-logarithmic regression the percentage effect is calculated by applying the formula $100\times\left(e^{\beta}-1\right)$ as stated explicitly for hedonic pricing models by Halvorsen & Palmquist (1980). Accordingly, in model (4), which is the basis for the following analysis, the highest green premium for energy efficiency class A+ is 3.98%, compared to the reference category. The following categories A, B, C, show a green premium of 2.43%, 2.12% and 0.80%, while for D, E and F, only very small differences of 0.3%, 0.1% and 0.2% were identified in comparison with the worst performing classes G & H.

4.6.2 Derivation of Marginal Benefit Curve and Marginal Cost Curve

In order to derive the marginal benefit of avoiding another unit of energy per square meter from the previously identified green premium, we proceed with the average square meter rent within the reference category, which is at €9.09/m^2. This is increased by the respective percentage of the green premium for the higher energy classes. The resulting increases in future cash flows are discounted to a net present value (NPV) using a yearly discount rate of 3% and assuming a 50-year useful life for the facility components. The discount rate reflects the investor's capital return requirement and would, in practice, vary according to the location or risk profile of the property. The assumption regarding the useful life of the building is based on the legal requirements of German tax law, which provides for straight-line depreciation at 2% per year, corresponding to a period of 50 years until the building is fully depreciated (§ 7 EStG para. 2). This NPV is finally divided by the absolute change in the energy performance index from each EPC class to the reference category, as stated in equation (4.3). This procedure yields the following plot which is presented in reversal scale in Figure 9. The step-by-step calculation can be derived from Table 20 in the appendix of this chapter.

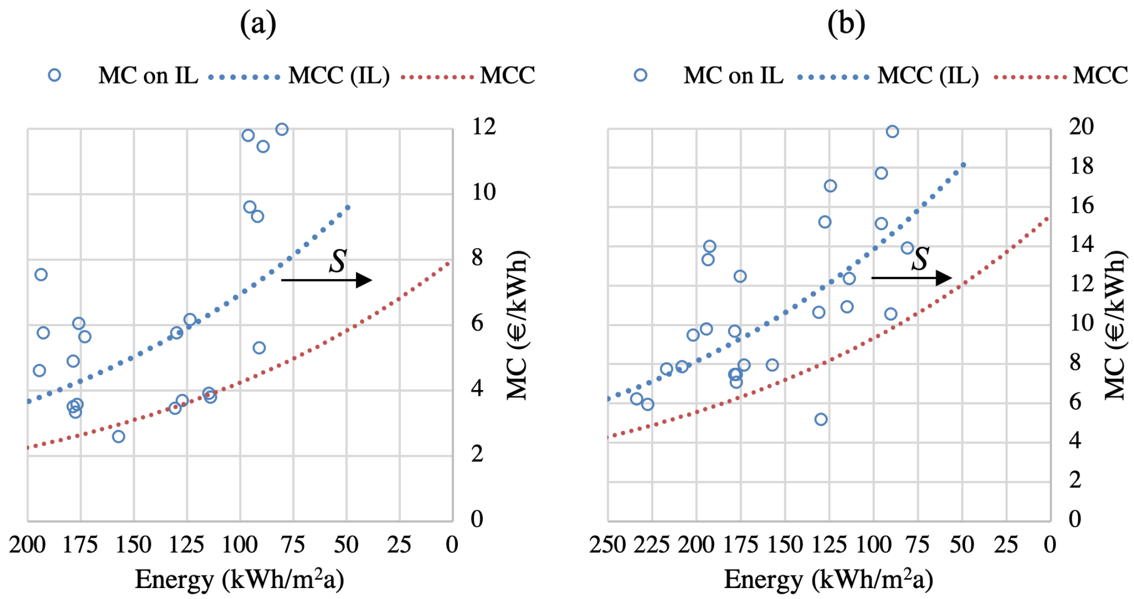
Figure 9: Derivation of the Marginal Benefit Curve



Source: Own depiction.

Following the procedure outlined in Section 4.5.2 and defined by equations (4.4) and (4.5), the marginal costs of energy demand adjustment are plotted against the intervention level (IL), as depicted by the blue circles in Figure 10a and 10b, where Figure 10a contains the values for the energy demand and Figure 10b contains the values for the actual consumption. The result suggests increasing marginal costs for retrofits on higher levels of energy efficiency for both cases, which has also been observed in earlier studies on energetic retrofits for different measures and materials (Timmons, Konstantinidis, Shapiro, & Wilson, 2016; Gustavsson & Piccardo, 2022). To adjust the MCC (IL) that was plotted on the intervention level to the target level to obtain the final MCC, it is shifted to the right by S (=83.46 kWh/m^{2}a for forecasted energy demand and =40.94 kWh/m^{2}a for actually measured energy consumption).

Figure 10: Derivation of the Marginal Cost Curve for energy demand (a) and energy consumption (b)



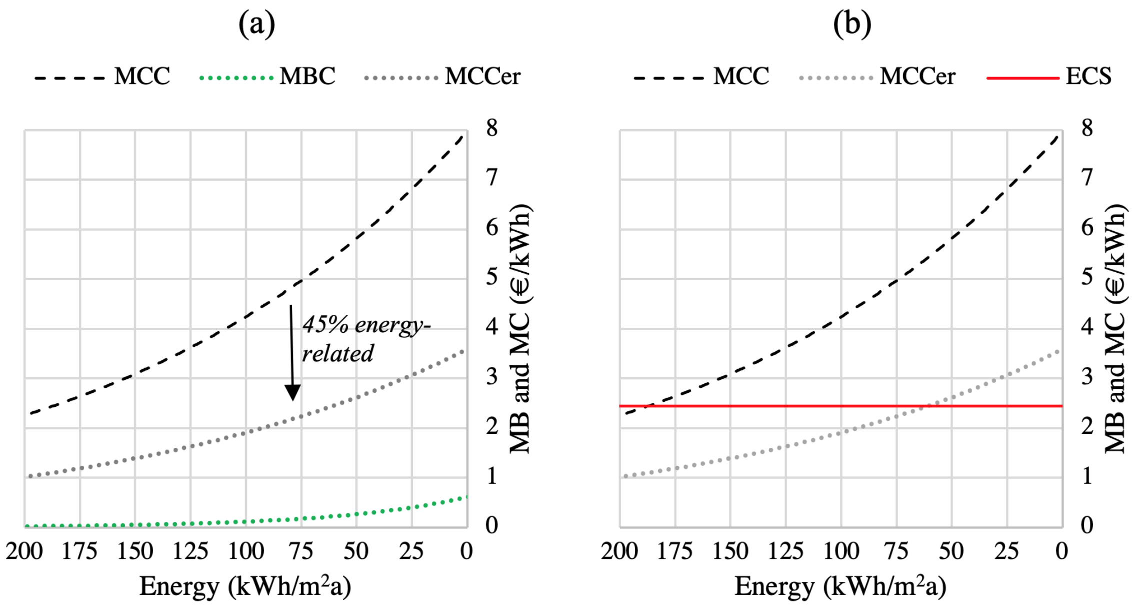
Source: Own depiction.

The comparison of the value range of the MBC and MCC already clearly shows that the costs exceed the expected benefits by far for both energy demand and energy consumption. Since the actual measured savings are on average far below the forecasted levels, the marginal costs related to consumption are at a higher level. In the following section, the analysis of the generated curves will be continued and extended by different approaches, in order to economically evaluate relevant interrelationships. Knowledge of a possible discrepancy between forecasted and realized saving should be considered in investment decisions for or against retrofits, but since data on the actual consumption is not available up front (and is therefore not part of an investor's decision-making), the analysis in the following sections is based on the energy demand values only.

4.6.3 Synthesis and economic evaluation of the CO_2 tax

The joint depiction of MBC and MCC in one plot yields the conclusion that the MB from possible rent increases is not sufficient to offset the retrofit costs from the landlord's point of view. The MBC runs under the MCC and does not intersect it. At this point, it should be noted that the preceding cost analysis is based on the full costs of the renovation measures, because only for 12 observations in the data set the costs eligible for subsidies for energy-efficient buildings ("förderfähige Kosten") are known. These costs are defined as costs for measures that explicitly increase the energetic quality of a building. For these 12 observations, the average share of energy-related costs is at 45% of full costs. Even assuming this percentage for all retrofits in the dataset and shifting the MCC downward by 55%, the observation of the irretrievability of the measures from the landlord perspective does not change. Also, the assumption-based Marginal Cost Curve for energy-related costs (MCCer; grey dotted line in Figure 11a) does not intersect the MBC (green dotted line at bottom of Figure 11a).

Figure 11: Marginal Cost Curves, Marginal Benefit Curve and Energy Cost Saving



Source: Own depiction.

The observation that energy-efficient refurbishment does not pay off in monetary terms applies in particular to rented housing, because of the split incentive problem. This is illustrated with a calculation example: To approximate the NPV of the reduction in energy consumption by one kWh/a, we assume the natural gas price per kWh of the year 2020 of 6.2 Cent/kWh (Destatis, 2022b), before the CO_2 tax on fuels was introduced in Germany, and calculate the total cost benefit over a 50-year useful life, applying the discount rate mentioned above and an energy cost progression of 2% which reflects the average annual increase for the years 2005 to 2020 (Destatis, 2022b). We assume the price and price progression for natural gas, because in the private household sector, natural gas is the most important energy source on the heating market, with a current share of around 44% (BMWK, 2022). This results in an NPV of €2.44 in terms of energy cost saving for one kWh/m^2. The corresponding line (ECS) intersects the MCC at an energy performance of about 185 kWh/m^2a, meaning that a retrofit would be expected to be economically advantageous up to this point (Figure 11b). This consideration assumes that owner-occupiers can retrofit at the same cost per square meter as the real estate companies that provided the data for the analysis. However this might in many instances not be the case, as these companies are able to benefit from economies of scale and bargaining power. The intersection with the MCCer, however is reached at a much higher energetic level at about 60 kWh/m^2a, due to the lower marginal costs.

The example does not claim to provide an exact estimation regarding the de facto profitability of retrofit measures in practice, as it is based on averaged data and various assumptions. Nevertheless, the insight is quite clear that undertaking modernization efforts to increase building energy efficiency is much more attractive, due to the inclusion of energy cost savings in the owner-occupied sector.

With the potential to solve the landlord-tenant dilemma to some extent, a proposal of splitting the CO_2 tax between tenant and landlord was included as a declaration of intent in the coalition agreement of the newly voted-in German federal government in 2021 (SPD, BÜNDNIS90/Die Grünen, & FDP, 2021). The agreement states that a percentage allocation of the tax will be implemented, that will depend on the EPC class of a building. If this law has not been passed by 1^{st} June 2022, the distribution will be made on a parity basis and regardless of the energy performance. Below, we analyse these two cases and again calculate a marginal benefit for saving one kWh of energy, but with inclusion of the carbon tax. One challenge hereby is that the CO_2 price, which is regulated in the BEHG ("Brennstoffemissionshandelsgesetz"), is only defined until 2026. In 2021, it was introduced at €25 per metric ton (t) of CO_2 and will gradually increase to €30 (2022), €35 (2023), €45 (2024), €55 (2025) and a range from €55 to €65/tCO_2 in 2026. Subsequently, free pricing is to be established on the market, unless it is decided in 2025 that defined price corridors will be continued.

The German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) uses values from the BMU-funded project "Politik-Szenarien IX" ("Policy Scenarios IX") in its current model calculations (Repenning et al., 2021). The "Policy Scenarios IX" project assumes a CO_2 price of €65/tCO_2 in 2026 and an annual increase of €15/t to €125/t in 2030, €200/t in 2035 and up to €275/t in 2040. We adopt this assumption and add the expectation that the price will not increase further from 2045, when Germany is expected to have already achieved net carbon neutrality. To calculate this tax on a kWh of energy, we include the CO_2 emission factor for natural gas of 0.20431 kg/kWh (Department for Business, Energy & Industrial Strategy, 2022). This conversion results in a kWh of natural gas being taxed, for example, with 0.73 Cents in 2022, with 3.0 Cents in 2030 or with 8.5 Cents in 2045 and after. The sum of the tax savings thus achieved for one kWh over a 50-year period results in an NPV of €1.10/kWh. In the case of parity distribution of the tax, simply 50% of the calculated NPV, i.e. 55 Cent, can be added to the MB for each EPC class, which shifts the MBC upwards.

In April 2022, the parties comprising the German government agreed on how the gradual allocation of the CO_2 tax for residential buildings should be structured. A 10-stage model is proposed, which provides that a poor energy performance of the unit or building leads to a higher cost burden for the landlord (BWSB, 2022). This is based on the energy consumption converted into CO_2 emissions, not purely on the EPC classes. The CO_2 costs to be borne by the parties per residential unit are determined via the heating cost statement. For apartments with a particularly poor energy balance (52 kg CO_2/m^2a), landlords bear 90% and tenants 10% of the CO_2 costs. However, if the building meets the very efficient standard, landlords do not have to bear CO_2 costs at all. To apply this information to our calculation methodology, which is based on EPC classes, we use the just introduced CO_2 emissions factor and multiply it with the average energy demand of each EPC class in our data (see Table 18).

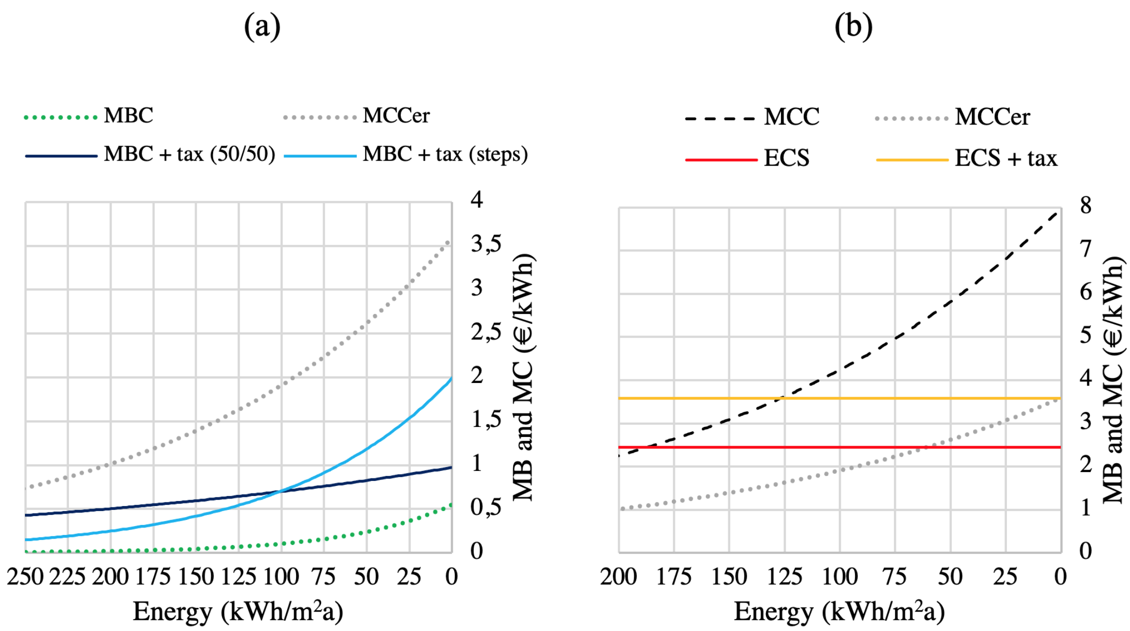
Table 18 Distribution of the CO_2-tax burden on tenant and landlord by EPC classes

Emissions (kg CO_2/m^2a)	Tax payed by Landlord (%)	Tax payed by Tenant in (%)	Approx. EPC class	Approx. emissions (kg CO_2/m^2a)
< 12	0	100	A+ & A	4.65 & 9.89
$12 \leq 17$	10	90	B	15.05
$17 \leq 22$	20	80	C	21.16
$22 \leq 27$	30	70	-	-
$27 \leq 32$	40	60	D	27.75
$32 \leq 37$	50	50	E	34.72
$37 \leq 42$	60	40	-	-
$42 \leq 47$	70	30	F	42.74
$47 \leq 52$	80	20	-	-
≥ 52	90	10	G & H	53.05 & 69.63

Source: BWSB (2022); own calculations.

Based on the input parameters just presented, the modified MBCs for the two different cases of imposing the carbon tax on the landlord are derived. These are shown in Figure 12a.

Figure 12: Influence of the CO_2-tax within the marginal cost analysis



Source: Own depiction.

The course of the MBC is increased significantly in both cases. However, the taxation is still insufficient to raise the marginal benefit of saving one kWh in the rental sector to such an extent that it offsets the cost of the renovation for any level of energy efficiency. Both MBCs that include CO_2 taxation also run strictly below the MCCer. In making this observation, it is important to note that the tax payments to be made in the future were discounted to 2021. The incentive effect of the tax would therefore also increase in influence, as the price rises over time. However, this is also partly countered by rising construction costs. From 2020-Q4 to 2021-Q4, construction costs for the maintenance of residential properties rose by over 14% (Destatis, 2022c). It is likely that if higher renovation rates are achieved, costs will also increase further, due to increased demand for construction services during the next decade.

In the owner-occupied sector, on the other hand, the tax would be fully added to the energy cost savings and thus further increase the economically reasonable depth of renovation (Figure 12b). In general, it is highly questionable whether both investors and private users would apply such assumptions in their decision making. The fact that the tax is only defined until 2026 and, as a consequence it is unclear how high it will be in subsequent years, creates planning uncertainty which limits the incentive effect of the carbon tax.

4.6.4 Limitations and possible model extension

Some limitations to the analysis, which mainly concern the data used, should be considered when interpreting the results. For the analysis of the green premium in the rental market, it is important to note that the rent data reflects asking prices which implies that there is no guarantee that a contract was actually concluded at this price. Nevertheless, as practice shows, leases in the residential sector are rarely negotiated and mostly conclude at the asking rent. Moreover, the data only extends to 2020. Accordingly, both the CO_2 tax and the recent tremendous price increases in the energy market in Germany of up to 30% (Destatis, 2022d) that might induce adjustments on the demand side, i.e. tenants being more sensitive to the energetic performance, are not reflected in this data.

Regarding the cost side of the analysis, due to the lack of information in the available data, it was only possible to make a rough approximation of the actual energy-related costs of renovation. It is important to note that with massively increasing renovation rates, which are a necessary requirement for reaching both the EUs' and Germany's climate targets, the typical occasion for energy-related renovation cannot always be "normal" maintenance, but rather intervention in the building substance outside of the usual maintenance cycles, in order to specifically implement the necessary measures for climate protection. For this reason, the application of energy related cost components alone in economic profitability studies can be criticized. A further limitation is that public subsidies from the federal programs for energy-efficient building renovation could not be considered, as they are not part of the provided data either. The observation of financially unviable retrofits from the landlord's point of view demonstrates that there is a substantial need for providing subsidies.

Finally, the analysis was based on energy demand per square meter, although the actual target value of the governmental goals does not refer to this, but to CO_2 or CO_2-equivalent emissions. While an approximation of the influence of CO_2 taxation could be achieved by means of a conversion using the emission factor for natural gas, the quantitative analysis would gain in substance if it could be based on actual CO_2 emissions per square meter. The current federal government has already expressed its intention to digitize the EPC and focus increasingly on CO_2, from which further research could benefit. But more importantly these steps would enable a more targeted implementation of retrofit measures in the future.

4.7 Conclusion

This study empirically investigated whether a green premium is paid for energy efficiency in the German rental market. The results show that this is indeed the case for the very high-performance EPC classes, while there is only a very small, almost negligible premium for mediocre- and lower-performance classes. In addition, a marginal cost curve for the abatement of an additional kilowatt-hour of final energy was derived from a dataset of green-retrofits of multi-family homes in Germany.

A comparison of the marginal cost with the marginal benefit derived from the identified green premium shows that the monetary advantage resulting from possible rent increases is far from sufficient to compensate for the costs of retrofit measures (if there are no public subsidies). While the finding of a green premium implies that the landlord-tenant dilemma is not absolute, but that landlords can also benefit to some extent from efficiency gains in relation to rent, a comparison shows that the net present value from energy cost savings would be many times larger than that of additional rent. An inclusion of the planned split of the CO_2 tax between both landlord and tenant in the analysis has shown that at the time of the study, this split is on average not capable of providing a sufficient incentive for the landlord to carry out green retrofits. The price per ton of CO_2 appears to be too low for this purpose. This statement does not imply that the taxation completely fails to achieve its purpose and has no influence on the retrofit activity, but it does imply that this form of taxation is not sufficient in the short term, to bring about a substantial increase in the renovation rate and that further measures are therefore necessary. It should be noted that an excessive increase in the tax to correct this and to increase the renovation rate in the short term is not an advisable measure, because this would drive up the housing costs of all households including those of owner-occupiers for which the incentive is already stronger than for owners of rental stock. Over time, as the tax per ton of CO_2 increases, the incentive effect will also increase. However, from today's point of view, the inclusion of the tax in calculations is associated with considerable planning uncertainty, as the price per ton is only defined until 2026. It should in fact be specified until 2030 and even beyond in order to take full advantage of realizable potentials that could be activated by CO_2 taxation. To increase the renovation rate in the short term and to focus on the worst performing buildings where the greatest efficiency gains are achievable, binding minimum standards as already proposed in the last update of the EPBD, appear to be a good alternative.

The study results, even if imperfect and subject to limitations, appear to be valuable not only for tenants and investors in their decision-making, but also for policy makers in the implementation of decarbonization efforts in the residential real estate sector.

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4.9 Appendix

Table 19 Full regression results for all variables

log(price/m^2)	**(1)**	**(2)**	**(3)**	**(4)**
Method	OLS	OLS	GAM	GAM
log(Energy per m^2)	-0.058***		8.047***	
	(0.001)		(edf)	
A+		0.134***		0.039***
		(0.002)		(0.002)
A		0.109***		0.024***
		(0.001)		(0.001)
B		0.069***		0.021***
		(0.001)		(0.001)
C		0.009***		0.008***
		(0.001)		(0.001)
D		-0.002**		0.003***
		(0.001)		(0.001)
E		-0.003***		0.001
		(0.001)		(0.001)
F		-0.002**		0.002*
		(0.001)		(0.001)
log(area)	0.774***	0.775***	8.988***	8.988***
	(0.001)	(0.001)	(edf)	(edf)
age	-0.001***	-0.0005***	8.993***	8.991***
	(0.00001)	(0.00001)	(edf)	(edf)
floor number	-0.00003	0.0005***	8.958***	8.898***
	(0.0001)	(0.0001)	(edf)	(edf)
number of rooms	0.031***	0.031***	8.970***	8.963***
	(0.0004)	(0.0004)	(edf)	(edf)
Elevator	0.031***	0.027***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Balcony	0.023***	0.024***	0.037***	0.037***
	(0.001)	(0.001)	(0.001)	(0.001)
Guests WC	0.043***	0.043***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Built-in Kitchen	0.064***	0.065***	0.063***	0.063***
	(0.001)	(0.001)	(0.0005)	(0.0005)
Garden	0.014***	0.014***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Cellar	-0.027***	-0.025***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Simple equipment	-0.077***	-0.078***	-0.085***	-0.085***
	(0.002)	(0.002)	(0.002)	(0.002)

log(price/m^2)	(1)	(2)	(3)	(4)
Method	OLS	OLS	GAM	GAM
Sophisticated equipment	0.141***	0.138***	0.118***	0.118***
	(0.001)	(0.001)	(0.001)	(0.001)
Luxury equipment	0.282***	0.275***	0.217***	0.217***
	(0.001)	(0.001)	(0.001)	(0.001)
log(Purchasing Power)	1.051***	1.029***	6.281***	6.137***
	(0.068)	(0.067)	(edf)	(edf)
log(Households)	0.109***	0.110***	1.082***	1.089***
	(0.008)	(0.008)	(edf)	(edf)
Spatial FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	533,780	533,780	533,780	533,780
Adjusted R^2	0.926	0.927	0.934	0.934

*Notes: Significant at *10, **5 and ***1% levels; standard errors in brackets below the estimated coefficient. edfs are reported for nonlinear estimates within nonlinear models. The estimated coefficients are marked with "edf" in brackets below. The reported significance shows the significance of smooth terms.*

Table 20 Calculation of marginal benefit for each EPC class

	A+	A	B	C	D	E	F
Green Premium (%)	3.98	2.43	2.12	0.80	0.30	0.10	0.20
Green Premium (€/m^2 p.m.)	0.36	0.22	0.19	0.07	0.03	0.01	0.02
Total Benefit (€/m^2)	112.28	68.58	59.91	22.68	8.48	2.82	5.65
ΔEpi (kWh/m^{2}a)	235.21	213.57	192.25	166.98	139.76	110.97	77.80
Marginal Benefit (€/kWh)	0.48	0.32	0.31	0.14	0.06	0.03	0.07

Notes: The green Premium in €/m^2 p.m. is calculated on the basis of an average rent of €9.09/m^2 p.m. in the reference category. The total benefit is calculated as the NPV of monthly payments over a 50-year period with bullet payments and a discount rate of 3%. ΔEpi always corresponds to the average change compared to the reference category.

5. Conclusion

The present thesis explores selected aspects that are relevant for the management of both direct and indirect real estate positions. With regard to directly held real estate, the focus of the research is on interrelationships regarding retrofit measures for the building, which represent a basis for adaptation to and mitigation of climate change and the associated climate risks. With regard to indirectly held real estate, extreme loss risks emanating from the financial and capital markets are investigated. Chapter 1 provides some background information and general motivation for the presented research topics. Chapters 2 through 4 contain the individual research essays comprising the cumulative dissertation. The following sections include a comprehensive summary of each individual research paper. Subsequently, congruencies, limitations as well as further research opportunities are considered.

5.1 Executive Summary

Paper 1 | The Value Effects of Green Retrofits

Renovating both public and private buildings is essential for driving energy efficiency in the real estate sector and thereby combating climate change (European Commission, 2022). Inadequate knowledge of the mechanisms behind retrofit actions and/or a lack of anticipation of potential value capture of green retrofits could delay intervention timelines or lead to the aborting of proposed retrofit actions, which should be of primary concern to policymakers and stakeholders tasked with the decarbonisation of real estate assets. Paper 1 offers both a conceptual framework and an empirical analysis, in order to identify the value effects of retrofits which can be derived from associated gains in energy efficiency. Moreover, the paper opens with an extensive literature review of green premia and presents previous research on both price effects on real estate transactions and the market for rentals. The evidence of a price premium is partly contradictory, but most studies find a significant positive effect of high environmental performance on market value. While numerous studies have investigated the upside value effects of energy efficiency in the real estate sector, there is little academic research that analyses the impact of green retrofits and the extent to which this can be capitalized by investors/owners. The conceptual framework that we have introduced helps to identify and measure three types of real estate value effects that can result from a green retrofit. First of all, and very much intuitively, an increase in value results from the avoidance of energy costs, which occur from an increase in energy efficiency. This effect should be evaluated differently for real estate transactions and rented stock, because, in the case of a property sale, the savings can be fully capitalized in value appreciation, whereas in the case of rented properties, this can only be the case if the rent can be increased proportional to the energy efficiency gain of the property. Another value effect results from increasing regulatory pressure with regard to the decarbonization of the economy. Future policy measures will lead to value reductions, as government penalties or market obsolescence can be expected for inefficient properties. A retrofit is capable of shielding the property from discounts and will therefore result in a net value gain. The third source of value relating to a deep retrofit with energy efficiency improvement is a cluster of so-called indirect benefits that vary from improved occupier wellbeing to reputational gains for the property users involved.

To strengthen the arguments put forward, an empirical analysis was conducted to demonstrate the positive value effect of higher energy efficiency in the real estate sector. The regression analysis based on 8,928 dwellings in the Munich residential real estate market includes a classic OLS approach to model the sales prices of residential units as a function of energy efficiency proxies and a set of hedonic characteristics. The results indicate value gains from energy efficiency improvements in the range of 2.4–7.4%, while the indirect benefits and reduced exposure to stricter standards amount to another 3%.

Paper 2 | Multivariate Tail Risk Modeling for REITs: What Factors Drive Extreme Losses?

Although some researchers already pointed out several years ago that research in this field could be fruitful (Liow, 2008; Stein, Piazolo, & Stoyanov, 2015) Paper 2 is the first study so far in which a dynamic multivariate EVT regression for REIT returns, depending on exogenous covariates, was modeled. After a general introduction to the statistical modeling of REIT return risk, the novel extreme value regression methodology is introduced, which is based on Chavez-Demoulin, Embrechts and Hofert (2016). We define extreme events using the POT method, where we set the threshold at the 25% quantile of the return distribution. Instead of simply fitting a GPD from the data series generated in this way, as is usually done, we include different covariates in the model fit of the distributions moments, namely scale and shape parameters. We identify model covariates by carefully reviewing the extensive body of literature on the risk factors for REITs. Since our empirical analysis is based on daily return data, several risk factors that are frequently highlighted in the literature, but for which no daily values are available, are excluded.

The data used as explanatories includes equity market covariates and bond market covariates. On the equity side, we use daily closing price returns from the S&P500, S&P600 small cap index, NASDAQ composite and the Dow Jones Industrial. Moreover, market volatility is captured by daily changes in the volatility index "VIX".

Accordingly, on the bond side, we construct two versions of the term spread and two of the risk spread in the bond market. Lastly, to proxy for interest rates and monetary policy, we use the federal funds rate. As the dependent in our model estimation, we utilize closing price returns of eight different NAREIT US indices, whereby we use five EREIT indices (All Equity, Office, Retail, Industrial, and Residential REIT index), three MREIT indices (NAREIT MREITs, Mortgage Commercial, and Mortgage Home Financing), and the combined All REITs index.

The estimation of a system of model specifications for each pair of dependent REIT index and exogenic covariate reveals several novel insights. Most importantly, the inclusion of covariates in the GPD fit yields improved model accuracy, as indicated by both the Log-Likelihood metric and the model residuals, which are closer to the theoretical quantiles if exogenic covariates are utilized. However, the explanatory power differs across the analyzed impact factors. In general, the equity market covariates for all REIT indices outperform the debt market covariates by far, meaning that the extreme value losses are more strongly driven by equity market than by debt market covariates. The best modeling result was achieved by including the S&P600. The asset class under consideration has no discernible impact on the applicability of the methodology, and we find no clear evidence that some covariates perform better for certain REIT asset classes indices than for others.

Paper 3 | Does Retrofitting Pay Off? An Analysis of German Multifamily Building Data

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Paper 3 analyses green retrofits, and is the first study in this context to examine the economic viability of such measures using marginal cost analysis. Although a large number of studies (including Paper 1) have shown that higher energy efficiency of buildings is associated with a green premium, it cannot be assumed that such increases in sales value or rent increases are sufficient to compensate for the costs of implementing retrofit measures. This is particularly questionable with regard to rentals, because, due to the landlord-tenant dilemma, not all value effects of green retrofits impact fully (Schleich & Gruber, 2008).

Two different data sets are used to investigate the research question. On the one hand, a hedonic pricing model is estimated for a large sample of more than half a million residential rental listings in Germany, which is in line with former research, shows a green premium for higher energy efficiency. On the other hand, a unique data sample with information on the retrofits of a total of over 1,000 residential units in multi-family homes is used to extract retrofit-related energy abatement costs. Based on the green premium detected by the hedonic pricing model, an economic benefit is calculated by computing the NPV of the rent increase due to increased energy efficiency for each of the EPC classes A+ to F, over the expected useful life. This NPV is again converted into a marginal benefit by dividing the total benefit by the energy savings per square meter. The results show a marginal benefit between 48 cents and 3 cents per kWh saved per year. By contrast, however, the marginal abatement costs of another kWh are much higher. These range roughly between one and four euros per kWh saved per year, if only energy-related costs are considered. This discrepancy between costs and benefits is highlighted by the fact that MBC and MCC do not intersect. A calculation of the NPV of the energy cost savings (from which a landlord does not benefit) shows that these have an NPV of roughly €2.40 per kWh, indicating that in the owner-occupied segment, the implementation of retrofit measures is much more attractive.

A further analysis step examines whether the inclusion of the recently announced, but not yet enacted regulatory measure of splitting the CO_2 tax on fossil fuels between landlord and tenant alters the result of the unfavourability of retrofitting. Accordingly, under serveral assumptions, the expected tax savings are computed as an NPV, which is added to the potential rent increase and thus shifts the marginal benefit curve upwards. However, even in this case, the marginal cost analysis shows that, on average, there is no sufficient incentive to implement renovation measures from a landlord perspective. The analysis reveals the importance of public subsidies and shows that, in addition to passing on the CO_2 tax to landlords, further steps are needed to increase the rate of renovation in the rented residential building stock in Germany.

5.2 Final Remarks

"Resilient investments are those able to withstand the effect of not only acute disruptions in the market but also chronic longer-term threats" (Clayton et al., 2021).

The economic case for real estate resilience is clear. Real estate managers who act on behalf of institutional investors have a fiduciary responsibility to not only identify risks that affect the assets they manage, but also to make investments that mitigate those risks and increase asset value. Clayton et al. (2021) further specify that risk management often relies on diversification and insurance to control risks, which is a valid and reasonable approach, but some long-term threats may not be insurable and may be nondiversifiable. Therefore, besides at the investment and portfolio level, much of the work to create resilient real estate portfolios must be at the asset level.

Although the individual articles in this cumulative dissertation are partly thematically distinct, they remain united by the fact that together, they address selected aspects of both short-term shocks and long-term threats, in line with the requirement described above to ensure resilient real estate investments. According to this understanding, Paper 2 refers to acute disruptions, while Paper 1 and Paper 3, with their reference to meeting the challenges of climate change, refer more to long-term challenges. More precisely, the EVT study on REIT returns extreme behavior can help investors and fund managers understand the distribution of real estate market returns better, so that they obtain potentially more accurate real estate return forecasts in times of crisis. However, the study is seen as a starting point on which further research needs to be conducted in order to convert the novel methodology into practical applications. The study has already shown that the inclusion of market data increases the accuracy of the fitting process, but a next step should be to compute actual risk metrics from the fitted distribution functions modeled using covariates, and to then compare the outcomes with the common method of distribution calculation by means of backtesting. Furthermore, within the modeling of the parameters themselves, there is ample scope for future research. The greatest potential in this regard is in the field of more complex multivariate models including a larger number of covariates. Additionally, the flexible modeling of the GAM functions could also enable incorporating interaction terms.

Retrofits of buildings are essential in establishing resilience to the long-term threats of global warming, as they mitigate climate risks and are suitable for adapting buildings to the changing market and regulatory environment. At the same time, it is clear that retrofitting existing buildings worth preserving, plays a central role in the transformation to a climate-neutral building stock in general (European Commission, 2022). A profound understanding of the rational decision-making process regarding green retrofitting, as well as possibilities regarding policy instruments to influence these decisions, are both necessary for policy makers to increase renovation rates to meet carbon reduction targets and for owners alike to protect or increase property values. Paper 1 and Paper 3 pick up on this aspect. In order to investigate the effect of improved energy efficiency, supply data on the sale and rental of residential properties in Germany was used. Actual contract data, that would ideally include multiple observations of prices for the same units at different points in time (before and after retrofit) would be even more desirable, but there are significant limitations to data availability. Therefore, for future research, value could be created by refining the analysis through data collection and quality assurance. This is particularly the case for assessments of the cost of actual efficiency gains through retrofits, especially with regard to the cost structure, i.e. the breakdown into full costs and the energy-related share. The plans presented by the new German government for the introduction of a digital building energy certificate, in connection with the focus on the characteristic value of the emission output instead of the energy consumption, will probarbly improve data availability (SPD, BÜNDNIS90/Die Grünen, & FDP, 2021). In addition, it may be useful to repeat the analysis of Paper 3 with updated data to re-evaluate the effect of the CO_2 tax split between landlord and tenant. Influencing variables such as energy prices, construction costs, and the level of the CO_2 tax itself, could significantly affect the results and make retrofits more favorable to rental property owners than is the case today. Extending the analysis to other real estate asset classes may also yield valuable insights.

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