Investing During Uncertain Times:
Factors Influencing Retail Real Estate Investments

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INVESTING DURING UNCERTAIN TIMES: FACTORS INFLUENCING RETAIL REAL ESTATE INVESTMENTS

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For my greatest and consistently motivating supporters,
my family.

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List of Abbreviations

AIC	Akaike Information Criterion
ARES	American Real Estate Society
AR(1)	first-order autoregressive process
AR(2)	second-order autoregressive process
BESS	Building Energy Submission System
CAPEX	Capital expenditure
CBD	Commercial Business District
c.p.	ceteris paribus
CDD	Cooling Degree Days
CFC	Chlorofluorocarbons
CO2	Carbon Dioxide
CO2e	Carbon Dioxide equivalent
CRREM	Carbon Risk Real Estate Monitor
DIC	Deviation Information Criterion
EF	Emission Factor
EGARCH	exponential Generalized Autoregression Conditional Heteroskedasticity
EMEA	Europe, Middle East and Africa
EPBD	Energy Performance of Buildings Directive
ERES	European Real Estate Society
ETS	Emissions Trading Scheme
F-gases	Fluorinated gases
GAM	Generalized Additive Model
GARCH	Generalized Autoregression Conditional Heteroskedasticity
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GJR-GARCH	Glosten-Jagannathan-Runkle Generalized Autoregression Conditional Heteroskedasticity
GRI	Global Reporting Initiative
HCFC	Hydrochlorofluorocarbons
HDD	Heating Degree Days
HFC	Hydrofluorocarbons

IPCC	Intergovernmental Panel on Climate Change
IPMS2	International Property Measurement Standards 2
IQR	interquartile range
kg	kilogram
kWh	kilowatt hour
LL	Log-Likelihood
MAC	Marginal Abatement Cost
Max	Maximum
MCMC	Markov-Chain Monte-Carlo
Med	Median
Min	Minimum
MLE	Maximum Likelihood Estimation
MRT	Mass Rapid Transit
MS GARCH	Markov-Switching Generalized Autoregression Conditional Heteroskedasticity
NCCS	National Climate Change Secretariat
NDC	Nationally Determined Contribution
N2O	dinitrogen monoxide
ODS	ozone-depleting substances
OLS	Ordinary Least Squares
pct	percentile
PFC	Perfluorocarbons
RBCF	Results-Based Climate Finance
REALIS	Real Estate Information System
RCA CPPI	Real Capital Analytics Commercial Property Price Index
SD	Standard deviation
SGD	Singapore Dollar
SBD	Suburban District
sq.ft.	square feet
TC	trans-critical
TEWI	Total Equivalent Warming Impact
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change

US	United States
USD	US Dollar
WAIC	Widely Applicable Information Criterion
yr	year

1. Introduction

1.1 General motivation

Unlike other property types, retail as an asset class is characterized by the high heterogeneity of its different forms of use. Supply-oriented retail properties, such as retail parks, hypermarkets, and non-food specialty stores, demonstrate high stability and investment security, among other things due to solvent retail corporations as tenants and long-term leases. In contrast, shopping centers, city centers and department stores have been struggling for years with declining sales and vacancies, driven by e-commerce and changing consumer demands (Kaiser & Freybote, 2022; Jones, 2010; Worzala et al., 2002). The aforementioned factors are just a few examples that can be assigned to retail properties' systematic market risk or unsystematic asset- and location-specific risk (Gondring, 2007).

Furthermore, retail real estate is likewise subject to market cycles and shocks, which have put massive pressure on the asset class. Specifically, the Covid-19 pandemic was challenging for tenants and landlords due to temporary closures of stationary retail, which led to rent deferrals, short-term rent defaults, but also to tenant insolvencies. In addition to disruptions in current cash flows, Hoesli and Malle (2022) found that the sector's prices, together with the hospitality market, suffered the most among commercial real estate during the pandemic. Regarding the war in the Ukraine and its associated uncertainties, real estate was relatively resistant compared to other investment classes (Będowska-Sójka et al., 2022). Still, the direct consequence, rising energy costs, also posed a challenge to the tenants and landlords of generally energy intensive retail properties. However, rising inflation and the end of the low-interest phase initiated by the central banks are likely to have a longer-term impact. The former is affecting the management and maintenance costs of retail properties, while on the tenant side there is primarily pressure from consumers' spending restraint. On the investor side, rising debt financing costs due to the interest rate hike and inflation-related increases in construction costs are leading to lower purchase price expectations. This has numerous effects on the overall real estate market, which cannot yet be fully assessed. Yet, markets with a higher price elasticity, such as the

UK, are already showing that devaluation of properties, redemption queues in funds, and increased selling pressure are possible consequences.

Since events such as the Covid-19 pandemic and the start of the war in the Ukraine are reflected in high volatilities in asset returns it is crucial for investors to constantly improve their risk management. **Paper 1** (chapter 2) aims to contribute to the literature of volatility modelling in the context of commercial – including retail – real estate.

Although the "old" risks described above have come back into attention today, the World Economic Forum (2023) forecasts a different focus in its latest Global Risks Report. The top four serve risks over the next ten years are classified as environmental risk, with failure to mitigate climate change at the top of the ranking.[1] This projection is consistent with the evaluations of the IPCC (2023), which states that countries' policies are not sufficient to mitigate climate change. Thus, it is likely that we will not be able to limit global warming below 2°C. Nevertheless, many countries are striving to comply with their Nationally Determined Contributions (NDCs) to the Paris Agreement and are continuously tightening national laws. The Energy Performance of Buildings Directive (EPBD) and the Taxonomy Regulation in the EU as well as the Enhancement and Standardization of Climate-Related Disclosures for Investors in the US are widely discussed and have a particularly strong impact on the real estate industry. As a result of this legislations, investors are facing high refurbishment costs to ensure that their properties are "future-proof". In the worst case, there is a risk of premature obsolescence of the building, because (future) regulations or market expectations can no longer be met. This scenario is known as “stranding”, or the object concerned is called “stranded asset”. With the Carbon Risk Real Estate Monitor (CRREM) Hirsch et al. (2019) introduced a sufficient tool to estimate the stranding year for specific buildings.[2] These risk considerations relating to sustainability regulations and changing market requirements are summarized under the term transitory climate risks.

[1] For comparison, the risk “Asset bubble bursts“ falls from rank 22 (2-year horizon) to 31 (10-year horizon).

[2] CRREM is aligned with SBTi, PCAF, EPRA, INREV and many other initiatives and organizations, and basis of several established ESG rating and benchmarking tools.

While the number of scientific papers highlighting the economic consequences of sustainability certification schemes, energy efficiency and CO2 emissions (e.g. Ooi & Dung, 2019; Cajias & Piazolo, 2013; Op ’t Veld & Vlasveld, 2014) have risen significantly over the past decade, there remains a gap in research examining the impacts of other greenhouse gases (GHGs). In addition to CO2, the unit CO2 “equivalent” (CO2e) encompasses the GHGs methane, nitrous oxide, and Fluorinated gases (F-gases). In Germany 87.7% of GHG emissions stem from CO2, while methane accounts for 6.7%, nitrous oxide for 3.9% and F-gases for 1.7% (Germany Environment Agency, 2022).[3] Although CO2 accounts for the majority of emissions, F-gases in particular should not be neglected, as the Global Warming Potential (GWP) of these is considerably higher. The use of those with GWPs of up to 5,000 is widespread, notwithstanding the existence of well-established technologies permitting the utilization of F-gases with lower GWPs or F-gas free alternatives. Interpreted, the GWP of 5,000 signifies that the contribution to the greenhouse effect of one ton of F-gas is 5,000 times higher than that of one ton of CO2. Thus, in many cases, the application of alternative technologies holds enormous potential to reduce F-gas emissions with less effort and cost compared to CO2. The Kigali Amendment of 2016 to the Montreal Protocol is an internationally recognized contract to reduce F-gas emissions ratified by 146 countries at present (United Nations Treaty Section, 2022). Some countries, with the EU leading the way since 2014 with the EU F-gas regulation, are implementing this contract in the form of phase-out plans. The volume restrictions on certain gases and the resulting price increases are intended to encourage users to invest in alternative technologies. However, akin to the dynamics observed in Emission Trading Schemes (ETS), the trajectory of price development remains uncertain, constituting a substantive price risk for customers.

The building sector plays a central role in the climate debate as it globally accounted for 34% of final energy consumption and about 37% of CO2 in 2021 (United Nations Environment Programme [UNEP], 2022), while the emissions from commercial buildings in 2019 averaged 73,4 kgCO2e/m2 (CRREM, 2020). In addition to CO2 emissions, the building sector is source of a high proportion of F-gas emissions, as these are used as refrigerants in refrigeration systems in buildings. In the European

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[3] Numbers refer to the year 2020.

Union the building sector was responsible for approx. 62% of F-gas emissions in 2019, similar to the US where F-gases from the building sector accounted for approx. 63% (United Nations Framework Convention on Climate Change [UNFCCC], 2022). From the UNFCCC's greenhouse gas inventory data it can be deduced that the share of F-gas emissions of the global average 73,4 kgCO2e/m2 of commercial real estate is 1.8% (CRREM, 2020). There is no evidence on the share of F-gases resulting from retail properties, but it can be assumed that it is significantly above 1.8% since retail – and especially food retail – relies heavily on refrigeration systems for food sales. **Paper 2** (chapter 3) aims to shed light on this topic as the level of F-gas emissions is significantly exposed to transitory climate risks.

Alongside the challenge of failing to mitigate climate change, the World Economic Forum (2023) predicts that the most significant risks will lie in adapting to climate change, as well as dealing with natural disasters and extreme weather events. Human-made climate change is already evident in the form of rising average global surface temperature (1.09°C higher in 2011-2020 vs. 1850-1900) and rising sea levels (on average 3.7 mm/yr between 2006 and 2018 vs. 1.9 mm/yr between 1971 and 2006). Furthermore, climate extremes such as droughts, heatwaves, tropical cyclones, or floods lead to significant losses and damages in the past and are projected to increase in frequency and intensity in the future. These trends are also referred to as physical climate risk (IPCC, 2023).

The retail real estate market is particularly exposed to physical climate risks. This can be attributed to the concentration in ground floor areas, which are the first to be damaged during heavy rainfall and floods. In addition to renovation costs, this can lead to temporary losses of rent or even long-term vacancy due to obsolescence of affected locations. Likewise, rising average temperature as well as heat waves are causing additional demand for cooling, which in turn means increasing energy costs, in order to meet consumer well-being requirements. Considering the potential extra costs, rational investors would intend to price in the expected losses into their investment activities. Real estate literature focuses mainly on the related price mechanisms in residential and office properties (e.g. Hirsch & Hahn, 2018; Addoum et al., 2023) and South-East Asia is geographically underrepresented. Therefore,

Paper 3 (chapter 4) provides evidence for the case of retail properties in Singapore and a potential discount for the associated flood risk.

In summary, this dissertation contributes to the real estate literature for the following risk factors with focus on retail assets:

- **Asset volatility** (Paper 1)
- **Transitory climate risk** (Paper 2)
- **Physical climate risk** (Paper 3)

The overall aim of this dissertation is to identify and quantify "new" climate risk factors and to improve the methodology for quantifying "older" risk factors for retail real estate investments. The ensuing subchapter provides information on the research questions used to achieve the objective of the work.

1.2 Research questions

The dissertation provides evidence on several research questions discussed in each paper individually. The following is an overview of these questions as well as further information on the co-authors of the papers, the publication status and conference presentations.

Paper 1

Deterministic or Stochastic? The Volatility of US Commercial Real Estate Returns

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(1) Do commercial property market features cause capital value returns to follow a deterministic or stochastic volatility process across time?

Authors	Cay Oertel, Chiara Künzle, Werner Gleißner, Sven Bienert
Publication status	Journal of Real Estate Research (Under review, 14 August 2023)
Conferences	37th Annual Conference of the American Real Estate Society (ARES), digitally (2021); 28th Annual Conference of the European Real Estate Society (ERES) in Milan, Italy (2022)

Paper 2

The Underestimated Global Warming Potential of Refrigerant Losses in Retail Real Estate: The Impact of CO2 vs. CO2e

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(1) Do F-gases have a statistically significant impact on the emission levels of food retail properties in Germany?

Authors	Chiara Künzle, Julia Wein, Sven Bienert
Publication status	Journal of European Real Estate Research (Accepted, 21 September 2023)
Conferences	38th Annual Conference of the American Real Estate Society (ARES), Bonita Springs, Florida, USA (2022)

Paper 3

Do Retail Property Markets in Singapore Ignore Flood Risk as a Natural Hazard?

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(1) Do markets account for the risk of sustaining property and financial losses in terms of their pricing mechanisms?
(2) To what extent are these risks represented in transaction prices empirically?
(3) Are these effects invariable over time, especially without any impact on market dynamics after flood events?

Authors	Jonas Hahn, Chiara Künzle, Cay Oertel, Jens Hirsch
Publication status	Journal of Real Estate Research (Under review, 14 August 2023)

1.3 Course of analysis

This cumulative dissertation is divided into the following sections for analysis. Chapter 2 starts off with the first research article "**Deterministic or Stochastic? The Volatility of US Commercial Real Estate Returns**", which focuses on the risk factor asset volatility. In detail, it proposes a new approach to model the volatility of retail and other commercial properties, namely stochastic volatility (SV) models. These differ from their counterpart – Generalized Autoregressive Conditional Heteroskedasticity

(GARCH) models – due to the assumption that the volatility process is stochastic and not deterministic across time. This can be attributed to the fact that the real estate market is inefficient and market agents behave irrationally. To compare the two approaches, the study employs several predictive information criteria to assess the superior goodness of fit.

Chapter 3 contains the second research article "**The Underestimated Global Warming Potential of Refrigerant Losses in Retail Real Estate: The Impact of CO2 vs. CO2e**", which deals with transitory climate risk. With the consumption data of German retail warehouses, it is examined to what extend refrigerants respectively F-gases account for the overall GHG emissions of the properties. Considering Heating and Cooling Degree Days (HDD/CDD) as well as grid decarbonization CRREM is used for the assessment.

In chapter 4, the third research article "**Do Retail Property Markets in Singapore Ignore Flood Risk as a Natural Hazard?**" provides evidence in the field of physical climate risks. Singapore's geographic location as an island and city state within South-East Asia leads to the situation that some retail properties are located in a flood prone area. Based on address-level transaction data it is analysed by means of a Generalized Additive Model (GAM) whether investors account for this physical risk in the form of price discounts. Furthermore, the influence of several flood events and potential damages are investigated.

Finally, the dissertation is rounded off in chapter 5 with a conclusion, which summarizes the results and gives final remarks.

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2. Deterministic or Stochastic? The Volatility of US Commercial Real Estate Returns

2.1 Abstract

This paper investigates the volatility dynamics of US commercial real estate appreciation returns. The study introduces the novel approach of stochastic volatility modeling to the literature of commercial properties. In contrast to the existing body of literature applying deterministic GARCH-based volatility models, their stochastic peers do not assume a deterministic volatility process across time. The study interprets the weak form of the efficient market hypothesis of property markets and irrational behavior of market agents as main theoretical drivers to advocate a stochastic behavior of the volatility of appreciation returns of commercial properties. Therefore, stochastic volatility models are estimated to model US real estate capital returns in addition to existing GARCH models which address the question of whether they follow a deterministic or stochastic process across time empirically. Subsequently, predictive information criteria are estimated to assess whether the volatility process entails stochastic features in the return time series. The empirical results show a smaller bias between the observed samples and the posterior predictive distributions in the stochastic models across various usage types in the US from 01/2001 to 12/2021. The extend of the improvements, however, differs across the analyzed property types.

Keywords – US Commercial Real Estate; Capital Value Returns; Stochastic Volatility; GARCH; Risk Modeling

2.2 Introduction and problem

The modeling of capital values and their volatility is of central interest for real estate academia as well as the industry as the capital value component of a property investment generally accounts for a large portion of the overall investment risk in commercial real estate. Thus, capital value volatility can cause substantial volatility of the overall investment position. In line with this, the literature has heavily focused on the innovative work of Engle (1982) and Bollerslev (1986) by applying univariate GARCH-based volatility models to account for the heteroskedastic nature of the volatility in time series of financial assets. In this context, for the capital value returns of alternative assets such as real estate, univariate GARCH conditional volatility models represent the dominant framework for both commercial (e.g. Miles, 2008) as well as housing properties (Dufitinema, 2020). However, deterministic GARCH models entail some crucial shortcomings especially within the context of real estate.

Most importantly, univariate GARCH models generally assume a fully *deterministic* relationship between the current asset return volatility and past returns as well as past volatility. Thus, this determinism in GARCH model specifications assumes the existence of constant model parameters, which model the relationship between volatility in any period of the data and past returns and volatility. This deterministic nature applies to the seminal symmetric models and asymmetric model extensions such as EGARCH (Nelson, 1991), GJR-GARCH (Glosten, Jagannathan, & Runkle, 1993) as well as their multi-regime Markov-Switching (MS) extensions (Gray, 1996). Especially for significant shifts or structural breaks in market volatility, single regime GARCH models fail to capture the true variation in volatility levels (Lamoureux & Lastrapes, 1990). These potential shifts are especially important for business cycles, which are subject to real estate's weak form market efficiency hypothesis and cycle theory (Kim & Nelson, 1999). The determinism of all specified types of models, however, appears to be in doubt as commercial property values. Instead, the named markets are notorious for unpredictable market changes and structural breaks in their time series data and their volatility (Zhou & Haurin., 2010), especially because of the abrupt market break during the Global Financial Crisis (GFC), its long-lasting low interest environment afterwards, and, very recently, the COVID-19 pandemic. Thus, real estate capital values appear to entail unobserved uncertainty, which can be interpreted as a rather stochastic component in capital value appreciation volatility.

Given the broad acceptance of GARCH conditional volatility models, however, how can one criticize these well-known and in widely applied models and turn towards alternative models such as the so-called *stochastic volatility* (SV) models (based on the seminal work of Taylor, 1982)? The decisive issue to advocate SV models is the interpretation of weak form market efficiency hypothesis as possibility to deny a *deterministic* volatility process and allow for a *stochastic* process instead. As noted above, commercial property appreciation has experienced several rather unanticipated market breaks and volatility shifts due to pricing uncertainty. One may argue that the MS GARCH models could offer a smooth solution to account for multiple regimes in the volatility process (which has recently been applied in a real estate context by Oertel et al., 2022). Nonetheless, even MS GARCH models still assume a deterministic relationship between the conditional volatility and the model covariates. Therefore, the present piece aims at the introduction of a novel SV model to treat the volatility of commercial property appreciation as a stochastic process. Thus, the central research question can be summarized as such: Do commercial property market inefficiencies cause capital value returns to be driven by a deterministic or stochastic volatility process across time? To shed light on this question, the following progression is applied: Firstly, we outline the relevant literature in the field of capital value return volatility of real estate. We then describe the alternative novel SV model. The ensuing section depicts the data on US commercial properties and its descriptive statistics. Next, the model calibration and Bayesian estimation and inference results for the benchmark GARCH models as well as the univariate SV models are reported. The final section concludes and proposes further research in the field of appreciation return volatility modeling of real assets.

2.3 Related literature and theoretical background of volatility dynamics

The volatility dynamics of commercial as well as residential property returns have been extensively studied in deterministic univariate GARCH model frameworks. Due to the majority of capital value volatility studies in real estate using deterministic models, they serve as benchmark models in this study to be tested against the novel and alternative methodological framework.[4] As noted by Gelman (2004), the methodology to model any given data should be able to capture the features and heterogeneities of the data such as non-linearity, time-varying properties, hierarchies, clusters, as well as latent variables. Therefore, the search for feasible methods appears to be legit for commercial real estate return volatility if current models are in doubt to capture the nature of the data in full.

The general approach to apply time-varying volatility models originates from the stylized facts of the underlying univariate return distribution of property capital values

[4] See the ensuing section for a full disclosure of the applied SV methodology.

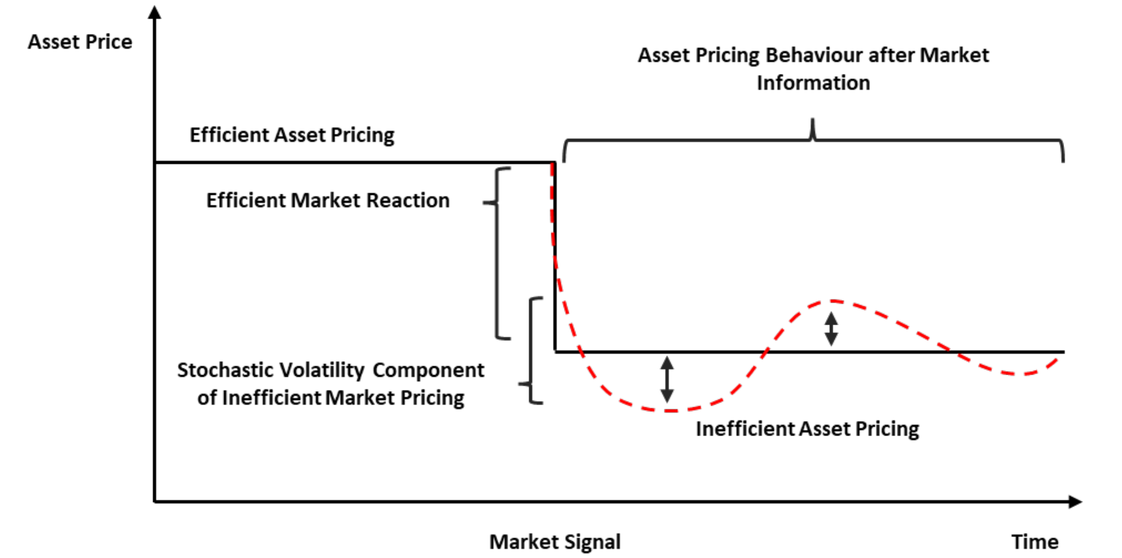
and its time-varying heteroscedasticity. As noted by Byrne and Lee (1997), Young, Lee, and Devaney (2006), Richter, Thomas, and Füss (2011), and Lee (2017) property value returns entail non-normality, skew, as well as excess kurtosis as univariate stylized facts across the entire return distribution. Regarding their inter-temporal features, Cont (2001) highlighted the importance of autocorrelation as well as volatility clustering. Accordingly, the described stylized facts and the heteroscedasticity in the appreciation return volatility of US real estate have been methodologically accounted for by applying GARCH models (Miles, 2008; Miller & Peng, 2006). Based on the seminal symmetric model, various asymmetric extensions have been applied to capital value returns of real estate to enhance the volatility modeling, including GARCH-in-mean (e.g. Stevenson, 2007), EGARCH (Lee, 2009), or EGARCH-in-mean (Morley & Thomas, 2011, 2016). These models, however, just like their symmetrical peers, assume a deterministic nature of the volatility process of the underlying assets. The main difference among the named models is the gradual adjustment in the deterministic specification on the right-hand side of the equation to model the conditional volatility. Yet all these studies stressed the limited explanatory power of the tested models.

As such, the decisive theoretical question to potentially endorse the application of SV in favor of the well-established deterministic models needs to be formulated as such: Is there a legitimate theoretical foundation of commercial real estate appreciation return volatility to be modeled by a deterministic process, which ties current volatility to past volatility and returns or should the volatility of capital value returns rather be modeled as a latent-space variable which allows the volatility to be a stochastic process across time?

The rationale of the study to extend the volatility modeling of commercial real estate builds on the market inefficiency and fundamental pricing hypotheses: As well-known from the literature, the efficient-market hypothesis does not hold true for property markets (Linneman, 1986). This applies for commercial real estate markets in particular because the specified markets entail features such as high transaction costs and information asymmetry among the agents (e.g. Gatzlaff & Tirtiroglu, 1995). As a methodological consequence, the market inefficiency hypothesis was used in real estate economics to advocate, first of all, the predictability of appreciation returns especially because of anchoring effects in the valuation practice (Liu & Mei, 1994), and, accordingly, a deterministic process of the accompanying return volatility. Nonetheless, the ability to model the general presence of this volatility clustering in the return time series in a parametric autoregressive model does not fully capture extreme or abnormal movements in the volatility process. For instance, Granziera and Kozicki (2015) underline the extraordinary unpredictability of appreciation movements for US real estate boom-bust cycle of the 2000s, which was hardly explained by fully-rational expectations of market agents. Indeed, the described irrational pricing is most likely generally caused by a large variety of human judgmental errors caused due to asymmetric information (Lei et al., 2001), asset price inflation illusion (Hayunga & Lung, 2011), and over-optimism (Abildgren et al., 2018) among the market agents. These findings are also backed by the survey study of Greenwood and Shleifer (2014) who find evidence for agents to expect higher returns after a protracted rise in capital values causing large yet not necessarily rational liquidity inflows of institutional investors. In turn, these inflows in commercial markets cause appreciation of the capital value of the assets, an irrational or unnatural prolongation of the cycle and ensuing abnormally abrupt re-pricing and capital value volatility. Hence, we conclude that especially commercial real estate capital values may move through different and more stochastically driven phases of volatility processes including structural breaks and irrational and ergo abnormal repricing and accompanying appreciation volatility (as explicitly reported by Barari et al., 2014). This variability and instability in the volatility process and the temporary breakdowns of underlying fundamental pricing and consequently unexplained appreciation return volatility appears to be a legitimate reason to model the appreciation return volatility stochastically and not simply deterministically.

Econometrically, we translate the weak form efficient market hypothesis into stochastic modeling by detaching unexplained temporary real estate capital values from market fundamentals. Basically, pricing theory states that asset prices are a function of exogenous factors (Stiglitz, 1990). This is also in line with the notes of Shiller (2003), arguing that even assets in imperfect markets generally follow a fundamental pricing component in the asset value. However, Shiller (2003) also argues that imperfect market assets also contain a behavioral component in the asset price. This component drives the pertaining asset values to experience phases in which capital value returns temporarily detach from macroeconomic fundamentals, move irrationally and eventually in stochastic fashion (see Figure 1). Explicitly for real estate, the divergence in macroeconomic data and appreciation volatility was observed by Glaeser et al. (2008). As such, a stochastic latent-space model may represent the logical methodological alternative to account for this unexplainable behavior of market agents to diverge from fundamental prices. Essentially, the econometric approach tests the presence of stochastic features in volatility as potential result of the weak form efficiency market hypothesis of real estate markets and their capital values. If stochastic features were present in the capital value returns, stochastic models are expected to capture these movements better than their deterministic peers.

Figure 1. Efficient market hypothesis and stochastic volatility component in asset prices (negative market signal)



Source: Own illustration.

For this methodologically opposing body of literature, namely SV models (based on the seminal work of Taylor, 1982), the number of empirical articles in real estate is relatively small and focused on the residential sector. In contrast to deterministic models and as the most decisive point to be applied to commercial property appreciation returns, SV models treat the volatility of the time series as a stochastic process. This stochastic nature of the process can potentially improve the capturing of structural breaks in appreciation return volatility processes compared to deterministic models. As noted by Bos (2012), the estimation of SV models is challenging in terms of non-linearity and due to the lack of standardized software packages. Chan and Grant (2016) mark the starting point for the applied Bayesian inference. Although Chan and Grant (2016) do not model real estate returns, the authors provide a highly valuable methodological approach by comparing the fit of deterministic GARCH and stochastic models. To do so, the authors intentionally refrain from a classic maximum likelihood estimation (MLE) procedure of the GARCH model but move towards a Bayesian estimation. The specified Bayesian estimation of the GARCH model ensures the comparability of the model with its stochastic peer since the latter can only be parameterized by Bayesian techniques, namely Markov Chain Monte Carlo (MCMC). Based on the Bayesian approach of Chan and Grant (2016) and for real estate returns, Dufitinema (2021) estimates a univariate SV model for Finnish housing price returns. The study, however, only compares the goodness of fit among different SV models. The decisive comparison of the present study between GARCH and SV models to assess whether real estate appreciation return volatility behaves deterministically or stochastically is not carried out. This comparison, however, is necessary to isolate the potential methodological value-add of SV models to capture the volatility dynamics of real estate returns in relation to well-known deterministic counterparts. Nonetheless, Dufitinema (2021) highlights the spatial heterogeneity of volatility dynamics among the 13 studied regions in Finland between Q1/1988 – Q4/2018, which will also be addressed in the present study using different spatial focuses. This spatial differentiation is in line with the rationale of Rapach and Strauss (2009) who state that coastal US property markets suffer from heavier structural breaks than interior states in the US. In addition to Dufitinema (2021), Yilmaz and Selcuk-Kestel (2018) not only study univariate SV models for housing price returns but they introduce the multivariate setting of SV models. In this class of models, the stochastic volatility is not only a process of its own variance process but is also affected by exogenous covariates. Yilmaz and Selcuk-Kestel (2018) formulate a rather reduced model for the S&P Case-Shiller Home Price Index and solely the mortgage rate between 1975 and 2016 as a co-factoring variable as they advocate a slim specification in the interest of avoiding multicollinearity among the covariates. However, volatility dynamics in a multivariate context require a solid theoretical foundation to legitimize the relationship between the volatility and exogenous covariates (Zhou & Haurin, 2010).

In sum, it can be stated that the literature concerning volatility modeling of capital value returns in real estate is heavily focused on deterministic GARCH models although SV models are theoretically in line with the market imperfections especially for commercial property markets. The present study extracts the potential to apply SV models to account for the outlined specifics of commercial property value returns. In order to close this gap in the related literature, the ensuing section formally describes the SV model and its GARCH benchmark to test against the target model in order to decide whether the appreciation return volatility is deterministically or stochastically driven.

2.4 The Bayesian SV methodology and the deterministic GARCH benchmark

The central empirical task to assess the nature of the volatility process in capital value returns is to test whether stochastic volatility models provide more accurate volatility estimates for commercial properties than their deterministic GARCH counterparts. For this purpose, the study estimates the novel SV models and the commonly known GARCH models as benchmark. Firstly, the SV model specifies $(\Omega, \mathrm{F}, \mathrm{F}_{t\epsilon[0,T]}, \mathrm{P})$ as a filtered probability space in which the capital value returns move. The model uses monthly commercial appreciation returns (y_t) as demeaned ($-\mu$) log returns of the commercial real estate capital values (CV_t):

$$\log\left({}^{CV_t}/_{CV_{t-1}}\right) - \mu = y_t \tag{1}$$

The basic SV model ("Plain Vanilla SV") represents the specified demeaned return series as a function of the following form (Taylor, 1982):

$$y_t = \sigma_t \varepsilon_t, \quad t = 1,2,\dots,T \tag{2}$$

$$\sigma_t^2 = e^{h_t} \tag{3}$$

$$h_t = \mu + \phi h_{t-1} + \sigma_\eta \eta_t \tag{4}$$

$$\varepsilon_t \sim N(0,1) \tag{5}$$

Where h_t is the latent stochastic process, μ a constant in the process, ϕ the persistence parameter, σ_η is the volatility of the stochastic process and lastly η_t denotes a stochastic shock. It needs to be highlighted, that the specified model represents the basic AR(1) specification since the relationship between h_t and exogenous covariates is limited to its first lag and a single persistence parameter. Within the relevant body of literature, Dufitinema (2021) illustrated the necessity to allow higher orders of autoregressive components in the equation of h_t. The present study follows the specified article by Dufitinema (2021) and allows for additional AR(2) relationships.[5]

The estimation procedure for the univariate does not follow a classic maximum likelihood procedure. In contrast, SV models are estimated using a Bayesian approach, based on the proposal of Kastner and Fruehwirth-Schnatter (2014) for the plain vanilla SV model. The approach follows a Markov-Chain Monte-Carlo (MCMC) sampling procedure. Since this Bayesian approach is the only available one for SV models, the assessed counterparts of GARCH models need to be analyzed by the same measures and not by classic Gaussian approaches (e.g. most dominantly MLE, as noted above). Hence, one needs to specify the prior distribution of the SV model hyperparameter vector $\theta = (\mu, \phi, \sigma_\eta)'$. For the prior distribution of the log variance the mean μ of the prior is set to zero and the variance set to one (based on the suggestion of Omari, Chib, Shephard, & Nakajima, 2007). The prior distribution of ϕ is set to five and 15. Lastly, the adjustable variance of the prior of hyperparameter for σ_η is set to one (both based on the default of Kastner, 2016). The burn-in period for MCMC iterations that are run but discarded is set to 1,000 and an ensuing number of 10,000 MCMC draws. A total number of four chains is calculated.

In contrast to the SV models described above, the specified GARCH models serve as benchmark to assess whether return volatility follows a stochastic latent process or a deterministic functional relationship. The general GARCH(p,q) model is specified as follows:

[5] Higher orders are generally denied due to the limited data point availability in direct real estate markets.

$$y_t = \sigma_t \varepsilon_t \tag{6}$$

$$\varepsilon_t = h_t u_t \tag{7}$$

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \tag{8}$$

$$u_t \sim N(0, h_t^2) \tag{9}$$

where σ_t denotes the conditional volatility, and ε_t are the residuals of the time series. The variable h_t describes the conditional standard deviation, being a function of previous errors where $\alpha_i \geq 0$ and previous conditional variances where $\beta_j \geq 0$. The error u_t is a sequence of i.i.d. random variables with mean zero, and its second moment equal to h_t^2. For the benchmark models of the present study, the parameters p and q are set to 1 (based on Hansen & Lunde, 2005).

Lastly, as the goodness of fit measure to compare the SV and GARCH models in a Bayesian framework, the study follows Gelman et al. (2014). In their study, the authors discuss various predictive information criteria to assess the goodness of fit of Bayesian models. Accordingly, the present study aims at predictive checks of the posterior distribution after the sampling (also referred to as *posterior predictive distribution)*. In order to isolate the differences between the models to fit the provided data (bias correction method), the posterior predictive distribution is assessed. The posterior predictive distribution $p(y^{rep}|y)$ is given by:

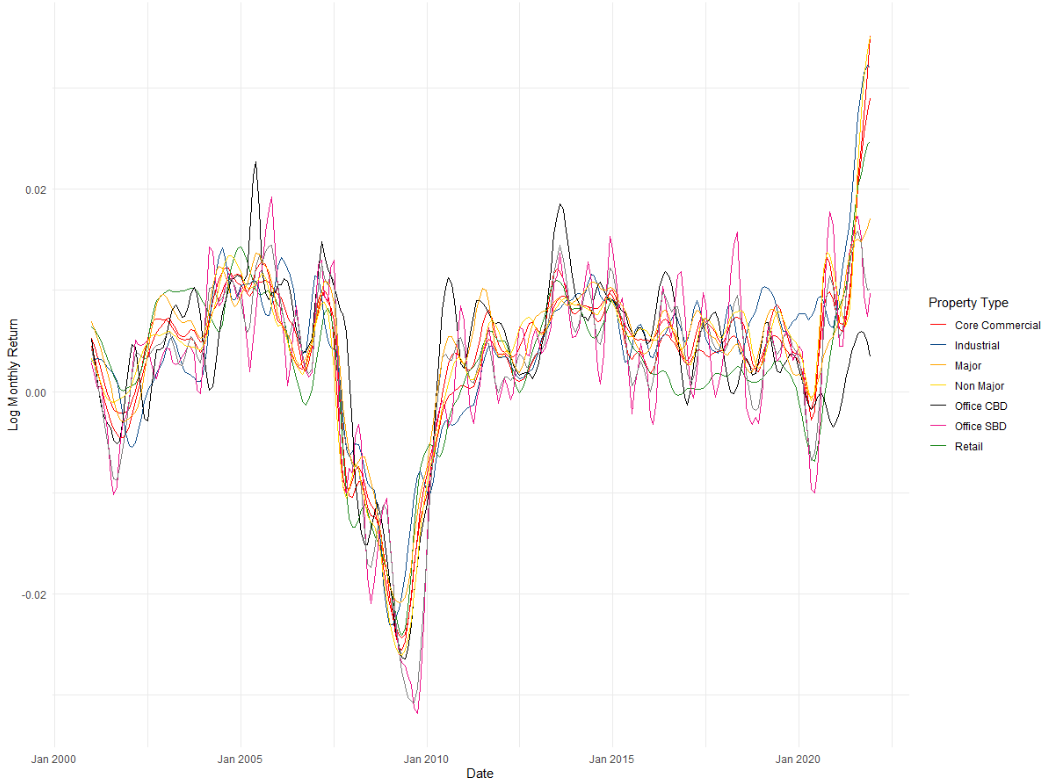
$$p(y^{rep}|y) = \int p(y^{rep}|\theta)\, p(\theta|y) d\theta \tag{10}$$

The predictive posterior checks in a Bayesian framework are made using the following numerical procedure: Firstly, the Bayesian estimation fits the model $p(\theta|y)$ to the observed data sample, namely the US appreciation returns of interest. The replications y^{rep} are then simulated from the joint posterior distribution $p(y^{rep}|y)$. Given these replications, a statistic $T(y)$ is designed to compare the generated samples with the actual observed return data (Gelman & Shalizi, 2013). Essentially, any systematic differences between the simulations and the observed data indicate potential failure in the model to capture the data generating process. The investigation and the correct data modeling to generate a volatility process of the return data, however, is at the core of the study. Bias correction techniques for the posterior distribution of the parameters in Bayesian inference include the Akaike Information Criterion (AIC, Akaike, 1973), the Deviation Information Criterion (DIC, Spiegelhalter et al., 2002, van der Linde, 2005), as well as the so-called Widely Applicable Information Criterion (WAIC, Watanabe, 2010) as quantities of $T(y)$. In addition to the outlined numerical procedures, we also provide graphical illustration of divergences between $T(y, \theta^s) - T(y^{rep\,s}, \theta^s)$ and the distribution of $T(y, \theta^s) \sim T(y^{rep\,s}, \theta^s)$. The former should include zero whereas the latter is supposed to be symmetric about the 45° line of the plot. Eventually, we interpret potential structural differences in the outcomes of $T(y)$ between GARCH and SV models as empirical evidence to support the respective modeling approach.

2.5 US commercial property return data and descriptive statistics

The empirical study uses monthly capital value log returns from the RCA Commercial Property Price Indexes (RCA CPPI) from January 2001 to December 2021, leading to 252 observations per capital value return series to estimate the volatility models. Since the study aims at identifying potential heterogeneity across the usage types in the US, nine indices will be modeled. Beside the National All Property Index, the usage types include the commercial, retail, industrial, office, office (Commercial Business District, CBD), and office (Suburban District, SBD) index. Regarding spatial differences, the major market index is discriminated from the non-major market index (as motivated by the study of Dufitinema, 2021). Therefore, the study uses a total number of 2,268 observations. The selection of commercial properties is mainly driven by the outlined theoretical rationale of market imperfections to cause commercial real estate return volatility to be non-deterministic. Secondly, the existing body of literature focuses solely on residential returns (e.g. recently Dufitinema, 2021). The graphical exploration of the data reveals the following courses for the return time series (see Figure 2).

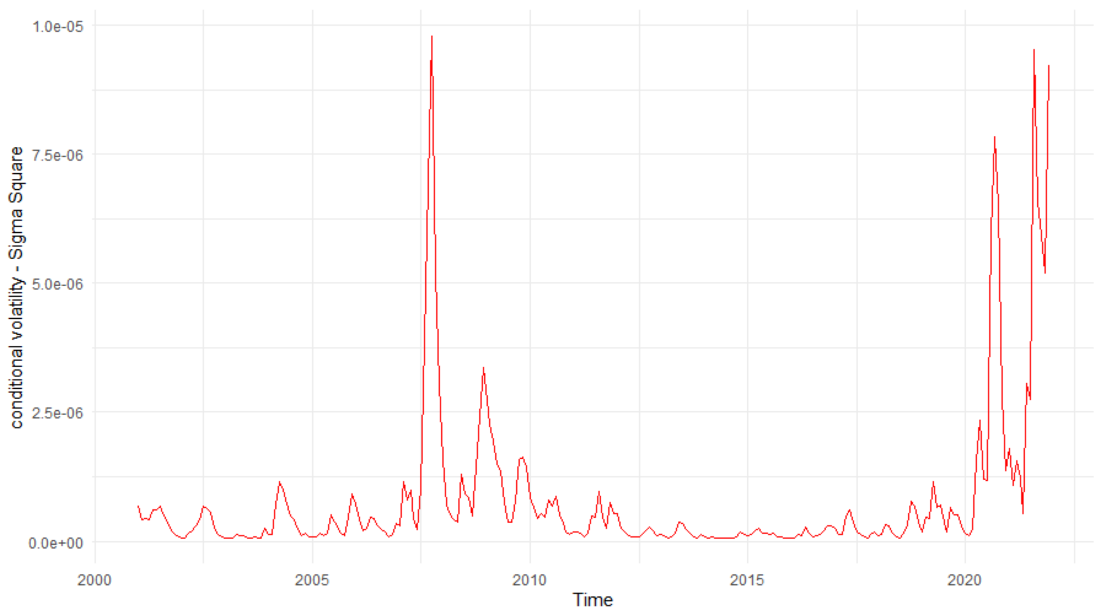
Figure 2. US capital value returns across time



Source: Own illustration.

The capital value returns in the data sample shows the typical shape of US commercial property market returns known from previous empirical investigations. From a theoretical point of view, especially the increased market volatility around the GFC 2008/09 as well as COVID-19 appears to be typical repricing and volatility phases (compared to Figure 1). To illustrate the increased volatility of this period, we plot the conditional volatility, measured by σ_t^2 from the deterministic GARCH benchmark as first illustration of the time series feature (see Figure 3).

Figure 3. Conditional volatility - US All National Index



Notes: For the sake of illustrative simplicity, the US All National Index was chosen. All time series in the data set show similar volatility features.

Source: Own illustration.

From Figure 3 it becomes apparent, that the specified market phases are empirically clearly more volatile periods, in which σ_t^2 exhibits clear spikes. In line with the theoretical explanation, the decisive question for the empirical model is, whether these spikes are deterministic or stochastic components of the volatility process. Despite the volatility, the monthly log returns of the observed usage types show a highly dependent course across time, with steady slightly positive returns close to zero from the starting point of the sample in 2001 until the GFC 2008/09. As known from previous research, the property price correction phase after the GFC caused heavy losses to commercial properties in the US, followed by a recovery period until 2012. The heaviest losses during the GFC were realized by office spaces in SBD areas. The lag between economic downturn and the realized negative returns in the observed data, however, is also subject to the illiquidity lag in the data itself. This illiquidity lag is caused by the timely difference between signing and closing of a transaction (roughly six months for institutional commercial real estate investors and corresponding investment processes). The relevant pricing in the signing process and the actual observation of the transaction can differ accordingly.

During the COVID-19 pandemic at the beginning of the 2020s, especially retail as well as office SBD suffered from capital devaluation. For retail the lower revenue from stationary retail and uncertainties surrounding the usage of physical space was because of pandemic-related retail restrictions including lockdowns. Since space reductions were mainly assumed for low quality offices spaces in non-CBD areas, the highest devaluations for office SBD are in line with market expectations during the pandemic. Remarkably, commercial cap value returns in the sample show a robust spike in appreciation returns at the end of the sample, i.e. after 2020. The only asset classes to fall short of this spike at the very end of the sample are office in CBDs and SBDs, having suffered heavily from work-from-home policies and shifts in office space demand during as well as after the COVID-19 pandemic. In contrast, especially industrial properties gained significantly during the COVID-19 pandemic due to larger consumption demand of non-stationary shopping and the consequent increased demand for industrial space including warehouses and logistics. From a numerical point of view, for the specified data sample, we obtain the following descriptive statistics (see Table 1).

Table 1. Descriptive statistics of the commercial real estate capital value returns

	n	Mean	Median	Min	Max	SD	
All National	252	0.0039	0.0054	-0.0244	0.0351	0.0083	
Core Commercial	252	0.0053	0.0072	-0.0228	0.0283	0.0081	
Retail	252	0.0030	0.0042	-0.0255	0.0290	0.0082	
Industrial	252	0.0026	0.0029	-0.0241	0.0247	0.0081	
Office CBD	252	0.0041	0.0051	-0.0231	0.0323	0.0084	
Office SBD	252	0.0035	0.0050	-0.0265	0.0227	0.0084	
All Office	252	0.0024	0.0040	-0.0319	0.0192	0.0094	
Major	252	0.0026	0.0042	-0.0308	0.0158	0.0088	
Non Major	252	0.0042	0.0055	-0.0209	0.0171	0.0072	
	Skew	**Kurtosis**	**Excess**	**1% pct**	**5% pct**	**10% pct**	**25-75 IQR**
All National	-1.0127	6.5846	3.5846	-0.0236	-0.0135	-0.0079	0.0053
Core Commercial	-1.3568	6.1516	3.1516	-0.0219	-0.0129	-0.0044	0.0069
Retail	-1.0567	5.9144	2.9144	-0.0244	-0.0132	-0.0088	0.0064
Industrial	-0.8537	4.7675	1.7675	-0.0227	-0.0138	-0.0069	0.0078
Office CBD	-0.4600	5.7499	2.7499	-0.0220	-0.0103	-0.0061	0.0076
Office SBD	-1.3878	5.5660	2.5660	-0.0253	-0.0148	-0.0052	0.0076
All Office	-1.3989	5.5489	2.5489	-0.0292	-0.0184	-0.0094	0.0093
Major	-1.7903	6.6815	3.6815	-0.0298	-0.0163	-0.0077	0.0068
Non Major	-1.6079	5.9084	2.9084	-0.0205	-0.0119	-0.0060	0.0060

Notes: 'Pct' denotes the alpha percentile of the return distribution. 'IQR' denotes the interquartile range between the alpha and beta percentiles of the return distribution.

Source: Authors own work.

For each of the first moment of the return distributions, we find positive mean returns across the sample. All return series show mean monthly log returns around 0.24 - 0.53%. The highest mean return was generated by the Core Commercial properties whereas the All Office time series exhibits the lowest mean return of 0.24% per month. The general positive appreciation return can primarily be explained by the stable economic environment. Throughout the entire data set, US commercial properties were affected by stable economic growth, particularly on grounds of an increased globalization. This economic environment, including the "technology change" due to strong digitalization, the resulting employment growth, as well as industrial production and domestic consumption, caused a robust demand side for US commercial real estate. Thus, the demand side supported appreciation through solid occupancy. On the supply side, on the other hand, the capital value appreciation of the existing stock was fostered because of constrained space supply throughout the sample. These constrains mainly arose from shortages in construction labor and material as well as price increases. Empirically, the supply side shortages peaked negatively in 2013 with stock growth below 1% for office, retail, and industrial properties. As such, from the perspective of the physical cycle of real estate, both sides of the market caused substantial rental growth to generate positive mean appreciation returns.

The second relevant cycle to property appreciation, the financial or investment cycle, also showed circumstances driving appreciation. Since commercial real estate generated positive returns in comparison to alternative fixed-income positions, US commercial real estate attracted liquidity throughout the entire sample. This development was mostly driven by the on-going yield compression of US 10-year treasury bills from around 4.60% in January 2001 to 1.35% in December 2021. Across the data sample, commercial properties generated positive spreads of 150 to 500 base points (Reid & Louw, 2021), causing a stable investment demand. The logic capital inflows into commercial real estate in turn caused a steady yield compression in all asset classes, sustaining capital values from the investment market side. Capital inflows came from all sectors of the investment horizon, including private, public, equity funds, other institutional, as well as an increase in cross-border investment activity. In this context, US commercial properties experienced additional inflows especially in the 2010s from EMEA, Asia Pacific, and the Gulf region (mainly by large sovereign wealth and institutional investment funds). These buyers, however, usually target large trophy assets in main investment markets such as Manhattan, Los Angeles, San Francisco and other major metropolitan areas. Suburban offices for example are hardly affected by these buyers. Nonetheless and in sum, physical as well as the financial cycle both created a favorable environment for commercial capital values to generate positive returns.

The minima of the data, however, express the highest losses for the All Office data, caused by the harsh repricing period after the GFC, as described above. During this period, US office properties experienced large decreases in rent growth as well as occupancy. Notably, the All National time series generated the highest maximum return per month of 3.51%. The maximum values for the returns are unanimously generated at the end of the data period (recall Figure 1 for graphical inspection). The standard deviation reveals a homogenous picture across the different time series around 0.07 - 0.08%. For the second moment of the return, distributions appear to be rather homogeneous across most of the data sample. The only time series to indicate a notably higher absolute standard deviation is the All Office series (0.094%). Since offices experienced the largest losses as well as recoveries over the course of the data sample (especially GFC and during the COVID-19 pandemic), this finding about the volatility of the All Office sample appears to be logical.

All time series entail a negative skew as well as excess kurtosis compared to the normal distribution. These empirical findings of leptokurtic and fat-tailed distributions are in line with the expectations about the distributional features, based on the literature review above. The returns also spread to a different extent around the center of their respective distributional probability mass, as indicated by the interquartile range between the 25 and 75 percent quantile. This range shows the lowest spread for the All National index at 0.053%. In contrast, the All Office index shows a range of 0.093%, meaning the largest spread between the inner 50% of the probability mass the returns. The other indices range around similar absolute values of 0.06 - 0.08%. Additionally, the bivariate analysis of the time series confirms the optical impression of strongly correlated returns (see Table 2).

Table 2. Bivariate statistics (Bravais Pearson correlation coefficient)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	All National	1.000								
(2)	Core Commercial	0.941	1.000							
(3)	Retail	0.981	0.879	1.000						
(4)	Industrial	0.916	0.826	0.938	1.000					
(5)	Office CBD	0.907	0.829	0.925	0.828	1.000				
(6)	Office SBD	0.768	0.699	0.806	0.761	0.668	1.000			
(7)	All Office	0.854	0.791	0.869	0.780	0.739	0.744	1.000		
(8)	Major	0.893	0.822	0.914	0.828	0.778	0.857	0.970	1.000	
(9)	Non Major	0.945	0.899	0.949	0.915	0.865	0.857	0.848	0.910	1.000

Source: Authors own work.

The Bravais Pearson correlation coefficient matrix displays the typically highly correlated return data of the analyzed property segments across time. The mean correlation coefficient across all asset classes of 0.869 indicates a strong yet expected co-integration of asset returns in US commercial real estate. Interestingly, we find the lowest cross usage type correlation for CBD and SBD office properties (0.668). Office properties in suburban areas are also generally the weakest integrated assets with a mean correlation across all other return series of 0.795. This finding is especially interesting from a portfolio diversification point of view. Retail, on the other hand, correlates the strongest with an average coefficient of 0.917 across all other asset classes. In sum, these correlation coefficients confirm the optical impression of Figure 1 and strong co-integration of the asset classes in the data set. This co-integration is logical in so far, as commercial real estate in general depends largely on similar macroeconomic drivers. Having investigated the uni- and bivariate features of the data, the ensuing chapter calibrates the deterministic and stochastic volatility models. This calibration tests for potential differences in the posterior predictive distribution and in the quantities of $T(y)$ of the stochastic approach in contrast to its deterministic peer.

2.6 Empirical model parameterization and robustness

For the described data, we parameterize the benchmark models as well as the stochastic counterparts, and we extract the goodness of fit for the relative models. Table 3 summarizes the empirical results for the deterministic and stochastic volatility models.

Table 3. Empirical results – goodness of fit measures

		GARCH	GARCH-t	GJR-GARCH	EGARCH	Plain SV - AR1	Plain SV - AR2
All National	**LL**	1406.82	1404.12	1406.81	1406.82	1428.92	**1426.91**
	AIC	-2803.64	-2798.24	-2803.62	-2803.64	**-2847.85**	-2841.83
	DIC	-2758.34	-2752.95	-2758.32	-2758.34	**-2802.55**	-2787.47
	WAIC	-2803.84	-2792.50	-2804.13	-2804.05	**-2818.36**	-2811.38
Core Commercial	**LL**	1421.96	1406.53	1421.94	1421.89	1420.64	**1434.52**
	AIC	-2833.92	-2803.06	-2833.89	-2833.79	-2831.28	**-2857.04**
	DIC	-2788.62	-2757.76	-2788.60	-2788.49	-2785.99	**-2802.69**
	WAIC	**-2836.44**	-2795.68	-2836.18	-2835.96	-2803.94	-2833.82
Retail	**LL**	1405.64	1422.18	1405.81	1405.72	**1442.69**	1442.27
	AIC	-2801.29	-2834.36	-2801.62	-2801.44	**-2875.38**	-2872.55
	DIC	-2755.99	-2789.07	-2756.33	-2756.14	**-2830.09**	-2818.19
	WAIC	-2795.76	-2829.18	-2797.45	-2796.13	**-2850.23**	-2843.73
Industrial	**LL**	1369.63	1360.59	1369.74	1369.65	1381.97	**1383.69**
	AIC	-2729.26	-2711.17	-2729.47	-2729.30	-2753.94	**-2755.39**
	DIC	-2683.97	-2665.88	-2684.18	-2684.01	**-2708.64**	-2701.03
	WAIC	-2733.31	-2704.41	**-2733.69**	-2733.25	-2718.70	-2722.01
Office CBD	**LL**	1288.21	1276.89	1288.14	1288.18	1298.40	**1317.28**
	AIC	-2566.43	-2543.78	-2566.29	-2566.37	-2586.81	**-2622.55**
	DIC	-2521.13	-2498.49	-2520.99	-2521.07	-2541.51	**-2568.20**
	WAIC	-2570.26	-2536.92	-2569.79	-2570.14	-2554.33	**-2590.89**
Office SBD	**LL**	1114.97	1103.11	1115.00	1115.01	1125.66	**1149.13**
	AIC	-2219.93	-2196.22	-2220.01	-2220.02	-2241.32	**-2286.27**
	DIC	-2174.64	-2150.92	-2174.71	-2174.72	-2196.03	**-2231.91**
	WAIC	-2224.02	-2186.22	-2224.19	-2224.30	-2212.13	**-2258.97**
All Office	**LL**	1251.12	1237.76	1251.17	1251.12	1259.52	**1278.85**
	AIC	-2492.25	-2465.53	-2492.35	-2492.23	-2509.05	**-2545.69**
	DIC	-2446.95	-2420.24	-2447.05	-2446.94	-2463.75	**-2491.34**
	WAIC	-2496.59	-2457.69	-2496.72	-2496.53	-2480.17	**-2518.34**
Major	**LL**	1408.35	1394.59	1408.30	1408.24	1406.15	**1437.94**
	AIC	**-2806.71**	-2779.19	-2806.60	-2806.47	-2802.29	-2767.89
	DIC	**-2761.41**	-2733.89	-2761.30	-2761.18	-2757.00	-2731.65
	WAIC	**-2809.93**	-2775.39	-2809.59	-2809.27	-2776.15	-2751.22
Non-major	**LL**	1429.06	1416.59	1429.09	1429.00	1432.73	**1496.83**
	AIC	-2848.12	-2823.17	-2848.18	-2848.00	**-2855.47**	-2785.65
	DIC	-2802.83	-2777.88	-2802.89	-2802.71	**-2810.17**	-2749.42
	WAIC	-2851.69	-2818.41	**-2851.82**	-2851.55	-2828.03	-2768.97

Notes: Bold numbers denote the superior model within a goodness of fit measure.

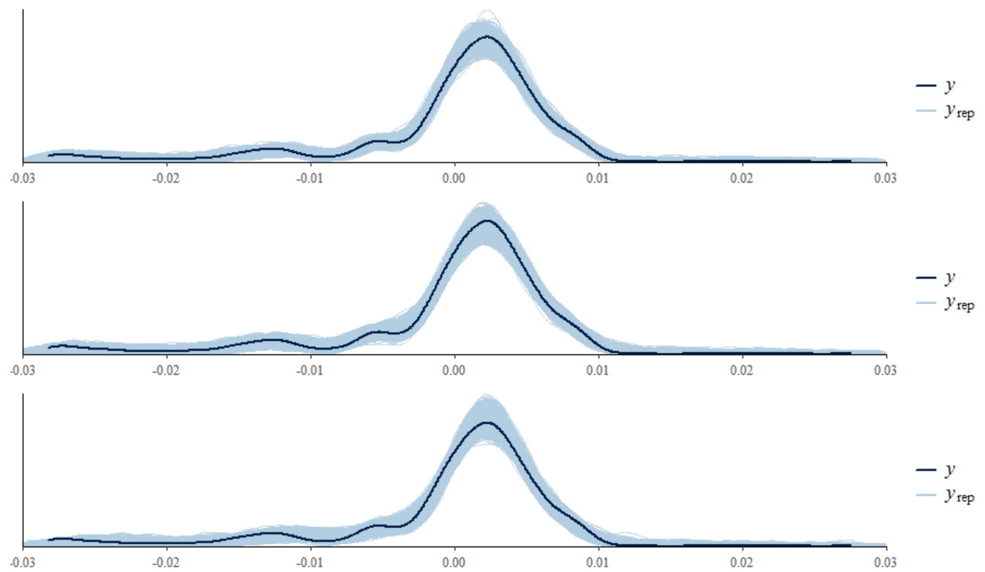
Source: Authors own work.

The results for the Log-Likelihood (LL) of the models report homogenous outputs for the goodness of fit to model the observed data. For all models, the SV models capture the empirical features of the data better than their deterministic peers. The LL reports the highest values for eight out of nine time series for the SV-AR(2) models and for one time series, the retail index, the highest value marks the SV-AR(1) model. Thus, as preliminary result, the LL can be interpreted as argument to advocate a stochastic approach to model the real property return data. Since the majority of models favor the AR(2) specification of the SV models, higher orders of autoregressive terms appear to be important for appropriate data modelling. As such, we find interesting empirical evidence in favor of higher autoregressive orders. Since the empirical results show structural outperformance of the AR(2) models compared to the AR(1) peer, these results' higher orders can be interpreted as a sign of higher persistence in the volatility process. Remarkably, the lowest likelihoods in absolute terms are generated by the office data series. These absolute values can be interpreted as generally challenging features of the volatility process. Furthermore, they demonstrate a higher level of unpredictability in the mentioned process compared to the other time series in the entire data set. These findings can be related to structural breaks in the volatility process, which is in line with the explanations on the history of US office markets mentioned in the previous section. Office capital value volatility in the US should hence be modelled with special care and may be subject to further detailed analysis. The other time series range in similar, and absolute higher LL values. This indicates a relatively higher fit and, given this, also a higher predictability of the volatility process across time.

Among the different goodness of fit measures – AIC, DIC, and WAIC – we find to some extent puzzling results. However, most additional measures confirm the capability of the SV models to capture the features of the data better than the deterministic peers. Only the major market time series shows a clearly mixed pattern: while the LL advocates for the SV model, all three remaining measures favor a GARCH relationship. Furthermore, it should be noted that the AR(2) approach in the stochastic model family may suffer from the additional parameter inclusion. The number of parameters is accounted for across the AIC, DIC, and WAIC indicators. Therefore, models with identical explanatory power and a higher parameter count suffer from penalization, ceteris paribus. We interpret this aspect of the results as a reminder to test various goodness of fit measures when deciding for an appropriate volatility model. However, the limited number of observations may contribute to the mixture of the results because the total number of 252 observations must be seen as typically limited property market time series length.

Regarding validation of the models, we investigate the graphical outputs and document posterior predictive checks. We use the All National data set to illustrate the diagnostic exercise for analyzing the posterior predictive distribution. These posteriors are essentially compared with the real data by graphical outputs. Firstly, we generate 500 random draws from the posterior distribution of selected models for the All National index. Models which capture the nature of the real data better are graphically closer to the density of real density than models which fail to predict the data well. The standard GARCH as well as the AR(1) and AR(2) SV models serve as analytical foundation. For the named models, Figure 4 displays the replicated data from the posterior predictive distribution (y rep, light blue draws) and the real data of the All National data (y, dark blue line).

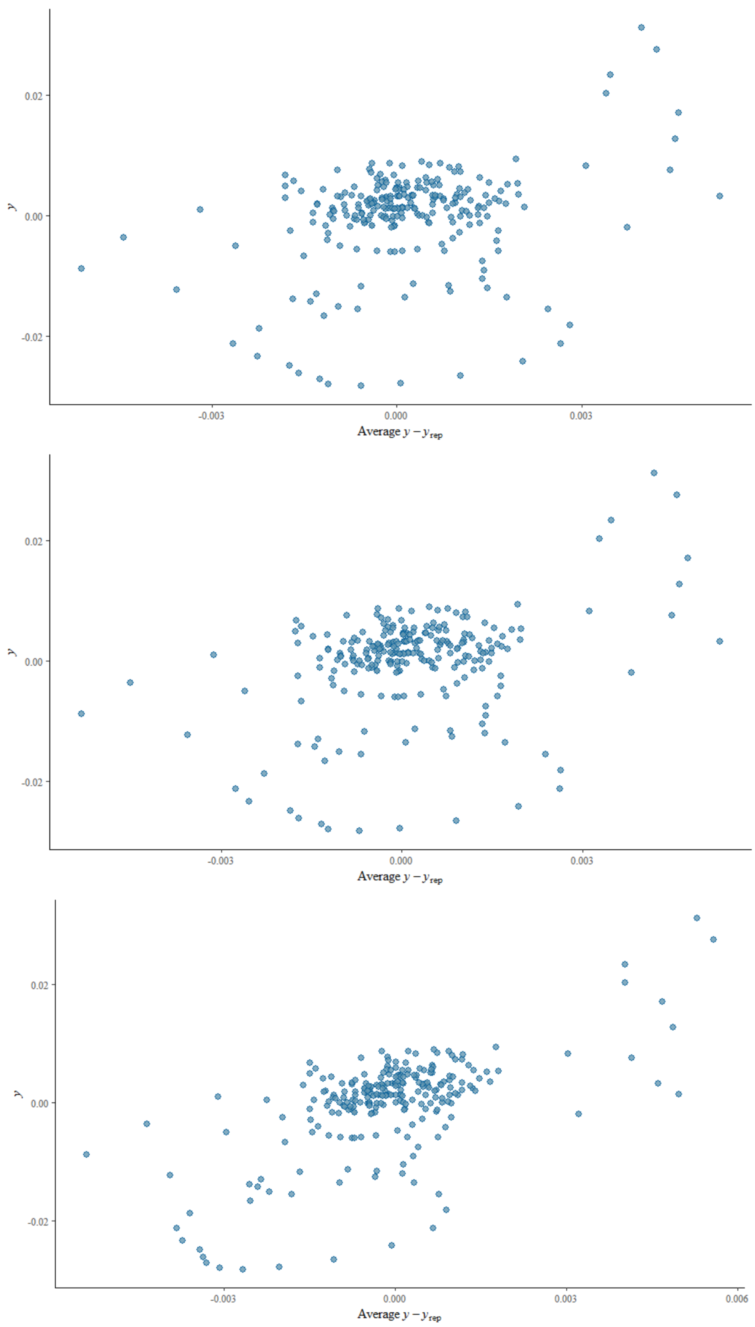
Figure 4. Posterior predictive distributions of GARCH (top) and plain SV – AR(1) (center), plain SV – AR(2) (bottom) vs. real data



Source: Own illustration.

For all three model types, we interpret the outputs as proof of a general feasibility to model the density of the real data as the replicated density of the data matches the real return data firmly. The illustration of the outputs reveals homogenous results between the GARCH and SV models as no substantial difference can be observed optically. Next, the model errors, i.e. the difference between replicated data and real data is assessed to validate the models in more detail and to check potential econometric problems in the models, e.g. due to non-normally distributed errors of the model. Therefore, we plot the average difference of y and replicated y against y itself because a non-linear relationship would reveal skew in the errors of the model and thus fail to represent, e.g., extreme values in the data generating process (see Figure 5).

Figure 5. Difference between replicated y and average y of the posterior predictive distributions of GARCH (top) and plain SV – AR(1) (center), plain SV – AR(2) (bottom)



Source: Own illustration.

The analysis of the diagnostic plots for the chosen models underlines the impression of the posterior distribution plots of Figure 4 and its homogeneity across the models. All models of interest show a centered distribution within the scatterplots around the center of the plot (x = y = 0.0). From the graphical illustration of the model errors, no econometrically harmful findings, such as harsh non-normality of the errors, need to be reported.

In sum, the empirical analysis of the investigated property return data reveals evidence to support the application of SV models to capture the nature of the real data in addition to deterministic models. In contrast to GARCH models, which specify present volatility as a function of past volatility and returns, SV models detach this relationship by introducing stochastic uncertainty to the process. For real estate, this stochastic component appears to be a valid component of the volatility process for commercial capital value returns. Volatility of capital values should, therefore, not be interpreted as a persistent and clustering process across time but rather a stochastic movement potentially caused by market imperfections. In the authors' opinion, the weak form of the market efficiency hypothesis can be used as a legit theoretical underpinning to validate the empirical findings. Especially the model parameter η_t can be interpreted as a profound stochastic shock to the volatility process (recalling equation 4). Among the SV models, higher orders of autoregressive components in the volatility process are of particular interest, because, in terms of likelihood, AR(2) specifications provide better goodness of fit than AR(1) models. Parameter sensitive goodness of fit measures, however, indicate the necessity to model the autoregressive order with care.

2.7 Concluding remarks and further aspects in volatility modeling of real estate

The present study introduces novel SV models for commercial real estate capital value returns in the US. The weak form efficient market and fundamental pricing theory hypotheses serve as the theoretical foundation for a potentially stochastic and not deterministic nature of the volatility process in commercial property appreciation. Essentially, irrational market agent behavior is a theoretical legitimization to detach the volatility process from deterministic relationships. Instead, the application of univariate stochastic volatility models is advocated due to the market imperfections specified. Subsequently, both deterministic as well as stochastic volatility models are estimated using a Bayesian approach and MCMC sampling techniques to ensure comparability. A total number of nine commercial property types in the US from 01/2001 to 12/2021 were analyzed. The data sample appears to be a legit time frame to cover different market phases including the GFC and the COVID-19 pandemic. We estimate the models in a Bayesian framework and generate posterior predictive distributions for all models. Posterior predictive distribution measures are applied to isolate the goodness of fit for the model classes, as proposed by Gelman (2004).

The preliminary empirical results of the benchmark GARCH model reveal heteroscedasticity in the volatility process (see Figure 3) as basic legitimization to apply conditional volatility models accounting for heteroscedasticity. This finding, however, is in line with previous studies on volatility dynamics in US commercial real estate returns. This study finds evidence for the existence of stochastic features in the data generating processes, since the data generating process rather follows a stochastic than deterministic process. This finding is isolated from the goodness of fit measures from the respective models in the empirical study. In sum, the empirical results support the hypothesis of stochastically driven volatility across the usage types in the data sample. We see reason to explain these by temporary detachment of stable macroeconomic fundamentals of commercial property because of market agent irrationality in weakly efficient property markets. The goodness of fit measures to isolate the differences across the model families in the study also indicate varying differences across the property types. The highest differences between deterministic and stochastic models are interestingly reported for office buildings, which went through the most complex and challenging business cycles across the data sample.

Future research based on this starting point in SV modeling of commercial capital value volatility may focus on three different aspects: Firstly, volatility studies in general should consider SV models as a legit methodological approach to model capital value volatility in contrast to GARCH-based. We see empirical evidence to extend volatility modeling for real estate by SV models. These models may also be incorporated in applied real estate management. Applications may include risk management practice to forecast capital value volatility. Since risk management is heavily focused on uncertainty modeling, approaches which can generate more accurate volatility estimates are of immense value. Secondly, not only capital value returns but also potentially other return metrics such as income or total returns can be subject to univariate SV modeling. As the present study neglects the cash flow component of the return, we see potential to assess this component as well. However, other real estate parameters, such as yields, rents, vacancy rates, etc. are potential target variables for SV models in a real estate context. Nonetheless, reasonable theoretical groundwork should exist to apply SV models to the specified parameters. Lastly, within the body of literature using SV models for real estate, especially the contribution of Yilmaz and Selcuk-Kestel (2018) can be interpreted as further motivation to use co-varying factors in a stochastic setting to study the impact of those on real estate. This could be especially fruitful for very recent data, assessing the impact of interest rate changes, as proposed by the two named authors for residential real estate in the US.

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3. The Underestimated Global Warming Potential of Refrigerant Losses in Retail Real Estate: The Impact of CO2 vs. CO2e

3.1 Abstract

Purpose – This paper investigates the impact of CO_2 vs. CO_2 "equivalents" (CO_2e) by analyzing fugitive emissions, with a particular focus on Fluorinated gases (F-gases), arising from refrigerant leakages in buildings. F-gases are an especially powerful set of GHGs with a global warming potential hundreds to thousands of times greater than that of CO_2.

Design/methodology/approach – The significant impact of CO_2e is tested by means of an empirical study with current consumption data from German food retail warehouses. This evaluation involves the analysis of the Carbon Risk Real Estate Monitor's country- and property-type specific pathway, coupled with a paired samples t-test to examine the hypotheses. The assessment is undertaken by evaluating the type of gas and the amount of leakage reported in the baseline year, subsequently converting these values to CO_2e units.

Findings – On average, F-gases account for 40% of total building emissions and nearly 45% of cumulative emissions until 2050. In light of ongoing climate change and the rising number of Cooling Degree Days (CDDs), it becomes imperative to assess both the environmental and economic impact of F-gases and to transition towards environmentally friendly refrigerants.

Originality/value – The analysis sheds light on the seldom-addressed threats posed by CO_2e emissions stemming from refrigerant losses. By identifying these threats, investors can devise strategies to mitigate potential future costs and carbon risks.

Keywords – carbon footprint; retail real estate; decarbonization; science-based targets; risk management; fugitive emissions

3.2 Introduction

At present 146 countries ratified the Kigali Amendment of 2016 to the Montreal Protocol (United Nations Treaty Section, 2023). They thereby collectively committed themselves to reduce the production and use of global Fluorinated gas (F-gas) emissions in terms of hydrocarbons (HFCs) by up to 85% by 2047 at the latest (United Nations Environment Programme [UNEP], 2020). This commitment signifies a shift from the singular focus on carbon dioxide (CO2) to the consideration of CO2 “equivalents”, known as CO2e, as a vital measure for limiting global warming to 1.5°C or 2°C.

In addition to CO2, four other greenhouse gases (GHGs) are significant in Germany. While CO2 constitutes the majority of GHGs released, at 87.7%, methane accounts for 6.7%, nitrous oxide for 3.9%, and F-gases for approximately 1.7% (German Environment Agency, 2022a).[6] Despite their lower percentage contribution, the significance of F-gases becomes pronounced when their respective Global Warming Potential (GWP) is considered. While CO2 has a GWP of 1, methane registers at 28, whereas F-gases can have GWPs exceeding 5,000 (IPCC, 2013). In essence, the impact of one ton of F-gases on the greenhouse effect can surpass that of one ton of CO2 by more than 5,000 times. The conversion into CO2e underscores the substantial leverage of these other greenhouse gases and the necessity of addressing them. Consequently, this presents opportunities for significant emissions reduction with relatively minimal effort and costs when compared to decarbonization plans for other GHGs. Conversely, neglecting F-gas emissions poses the risk of distorting or overestimating emission balances, impending climate mitigation efforts.

The building sector plays a central role in the climate debate as it globally accounts for 34% of final energy consumption and about 37% of CO2 in 2021 (United Nations Environment Programme [UNEP], 2022). Furthermore, the sector is a notable contributor of F-gases emissions, particularly of HFCs, commonly used as refrigerants in refrigeration and air conditioning equipment that can release these gases into the environment due to leaks. In 2019, the European Union emitted approximately 84.6 million tons of CO2e from refrigerants, with over 60% stemming from the building sector. In Germany, roughly 38% of F-gas emissions in 2019 were associated with refrigerants used in the building sector, while in France, this figure stood at around 51%. Whereas this is below the EU value, the shares in other member states, such as Portugal with 76%, are significantly higher. The variance in these percentages can be

[6] Numbers refer to the year 2020.

attributed to the prevalence of stationary air conditioning systems for the cooling of rooms and entire floors in countries with warmer climates. In Portugal, these systems alone account for 40% of F-gas emissions in the building sector. In contrast, in Germany, where such systems are less common, stationary air conditioning systems contribute only 15% to F-gas emissions in the building sector (United Nations Framework Convention on Climate Change [UNFCCC], 2022).

In the real estate sector, the food retail asset class holds a distinctive position due to its substantial electricity consumption and the prevalence of large, centralized refrigeration systems. As of 2020, over 60% of central refrigeration systems in Germany still use environmentally harmful refrigerants. The recorded filling volumes reveal that new or revitalized systems in discounters and small supermarkets are increasingly opting for alternative refrigerants, but large supermarkets tend to continue using high GWP refrigerants even for new installations (German Environment Agency, 2021). However, reliable data on the share of F-gases in the overall emissions balance of supermarkets is limited. Coop Sweden states that refrigerants are responsible for 16.5% of emissions as of 2015. The Swedish supermarket chain ICA puts refrigerants at 31% of total emissions as of 2015 (Karampour et al., 2016). Lidl Germany's sustainability report shows that the company was able to significantly reduce F-gas emissions by approximately 46% between 2018 and 2020. Looking at the total Scope 1 emissions, the F-gas share decreased from approximately 27% to 17% (Lidl Dienstleistung GmbH & Co. KG, 2021). Given this context, the paper poses the following research question: Do F-gases have a statistically significant impact on the emission levels of food retail properties in Germany?

Following the introduction, the paper provides further background on regulatory frameworks, including phase-down regulations, and reviews existing academic literature. Subsequently, it describes the research design, which involves the Carbon Risk Real Estate Monitor (CRREM) and a paired samples t-test. The analysis is conducted on a German food retail portfolio compromising 29 assets, with data and descriptive statistics discussed. The results are then presented at both asset and portfolio level to emphasize the impact of F-gases on the overall emissions of retail properties. Lastly, a conclusion and outlook are provided.

3.3 Literature review and background

From a technical point of view, F-gases are produced specifically through chemical processes and are then sold as operating materials for plants. The emissions, which pose a significant threat to the atmosphere, primarily occur during two critical phases: firstly, in the operational stage, where these gases escape from the essentially closed cooling circuits due to leaks within the refrigeration system, and secondly, during the disposal (Bortolini et al., 2014). Although stringent monitoring and maintenance efforts aim to minimize leakage rates, new refrigerant still has to be added regularly during maintenance. Consequently, this refill quantity corresponds exactly to the quantity that escaped from the system and is ultimately released directly into the environment.

From a chemical standpoint, refrigerants can be classified into distinct substance groups. These include partially fluorinated hydrocarbons (HFC), perfluorinated hydrocarbons (PFC), chlorofluorocarbons (CFC) and partially halogenated chlorofluorocarbons (HCFC). It is worth noticing that the latter group, HCFCs, stands out as ozone-depleting substances (ODS), representing a direct hazard to the ozone layer. Consequently, owing to their profound environmental impact, HCFCs have been prohibited, leading to the adoption of HFCs and PFCs as alternative refrigerants. For a comprehensive understanding of the commonly used F-gas based refrigerants, Table 4 provides an overview including their respective GWP.

Table 4. Selected F-gases and their GWP

F-gas	GWP_{100}
R-404A	3,922
R-407C	1,774
R-410A	2,088
R-422D	2,729
R-448A	1,387
R-449A	1,397

Source: Author representation based on German Environment Agency (2022b).

The reported data in the national greenhouse gas inventory on emissions caused by refrigerants includes the categories "Commercial refrigeration" and "Stationary Air-conditioning", which can be allocated to the real estate sector and account for 38% in Germany (United Nations Framework Convention on Climate Change [UNFCCC], 2022). In terms of total commercial space in Germany, this equates to an average F-gas emission rate of 1.33 kgCO2e/m2. When compared to the overall emissions from commercial buildings in 2019, averaging 73,4 kgCO2e/m2, F-gas emissions represented a mere 1.8% of the total (CRREM, 2020). However, specific data on the proportion of F-gas emissions for retail properties within the commercial real estate sector is unavailable. It is reasonable to assume that the share of retail, and particularly food retail, exceeds this 1.8% benchmark. This assumption is founded on the fact that, as of 2020, 60% of central refrigeration systems in large supermarkets still operated using high GWP refrigerants (German Environment Agency, 2021). This is further supported by the disclosure of the food retailer Lidl, which reported a share of 17% of F-gases emissions in 2020 in Germany, significantly exceeding the benchmark of 1.8% (Lidl Dienstleistung GmbH & Co. KG, 2021). This disparity is of paramount importance for real estate professionals, as quantifying this issue is the first step towards being aware of it. Environmentally friendly refrigerant alternatives are available on the market and tighter regulations are encouraging a conversion to them. Climate-friendly propane (GWP of 3) and CO2 are particularly promising in this context. However, transitioning to alternative refrigerants is associated with retrofits to the system or new acquisitions and in turn substantial CAPEX costs. The absence of precise figures on the share of F-gas emissions leaves real estate professionals unable to estimate the extent of these additional costs.

In 2019, the Kigali Amendment, which was added to the Montreal Protocol, came into effect, obliging countries to drastically reduce HFCs by no later than 2047 (United Nations Environment Programme [UNEP], 2020). The EU has already pre-empted the Kigali Amendment by enacting an F-gas regulation in 2014. It encompasses usage bans and a "phase-down" mechanism, which gradually restricts the sale of HFCs (Regulation [EU] No 517/2014, 2014). The artificial supply shortage aims to generate price increases on the market, thereby rendering alternative refrigerants more appealing to purchasers (see Appendix for further details). Due to the high growth of the market for air conditioning and heat pumps as well as to achieve the goals of the Kigali Amendment, the EU regulation will be amended soon. The revisions will include an accelerated phase-down and stricter usage prohibitions. The US (see American

Innovation and Manufacturing Act of 2020, 2020), along with other nations like Singapore and Australia, are now adopting similar phase-down programs.

From a reporting perspective, a mixed picture emerges regarding the level of awareness among market participants. Companies generally refrain from addressing F-gas issues unless specifically prompted to do so in their operational activities. For instance, the Global Reporting Initiative (GRI, 2021) includes a comprehensive "Disclosure 305 Emissions" category that mandates detailed reporting of all GHGs by scope. A look at the latest published sustainability reports according to GRI shows that while food retailers diligently adhere to these guidelines, real estate owners of supermarkets focus solely on CO2 in their reporting. The technical assessment criteria (of the first environmental objective) of the EU Taxonomy Regulation, which has been in effect since 2021 and applies, among other things, to green real estate funds within the European Union, is divided into new construction, existing buildings, renovation, and individual measures, without any limitations based on CO2e. Solely for new constructions exceeding 5,000, a GWP assessment is mandatory for each life cycle phase (Regulation [EU] 2021/2139, 2021).

Academic real estate literature predominantly explores the economic implications of high F-gas consumption at the asset level, particularly the trade-off between low GWP refrigerants and associated additional costs. However, it neglects the role of F-gas emissions in decision-making processes related to transactions, asset allocation and the development of decarbonization strategies for real estate portfolios. For adjustments in the decision-making process, the actual F-gas share for the respective property must be known. The existing literature described in the following can only assist after the need for action has been identified. Nonetheless, it is valuable to provide a brief overview of this academic literature to underscore the challenges faced by real estate professionals once they have quantified the additional emissions.

One noteworthy decision-making metric is the Total Equivalent Warming Impact (TEWI), which assesses the total CO2e emissions of direct (F-gases) and indirect (electricity) emissions throughout the lifetime of a refrigeration system. Given that the electricity consumption of refrigeration systems is typically increasing when low GWP refrigerants are employed, the TEWI accounts for the intricate interplay between the direct and indirect emissions (Islam et al., 2017; see Appendix for a calculation example). Hart et al. (2020) conducted a marginal abatement cost (MAC) curve to determine whether retrofitting existing systems to use refrigerants with lower GWP (e.g. R-449A) or replacing them entirely with systems utilizing alternative refrigerants (e.g. CO_2) is the more economically viable option. They found savings of 45% CO_2e at 9% of abatement costs when opting for R-449A (GWP 1,397) instead of investing in a new CO_2-based system (Makhnatch et al., 2017). Nevertheless, rising operational costs for the increasingly popular R-449A must be factored into the equation due to anticipated purchase price increases within the phase-down mechanism.

Presently, property-related carbon risk assessments do not account for such price increases or other transitory risks, such as a carbon price on F-gases. Carbon pricing mechanisms, employed in various countries and sectors in diverse forms, aim to incentivize abatement costs for emission (Liu et al., 2017). Possible instruments include carbon taxes, emissions trading systems (ETS), crediting mechanism, results-based climate finance (RBCF), and internal company carbon pricing (shadow price and internal carbon fee). Oertel et al. (2022) have modelled the volatility of carbon price risk for real estate. This is measured using the European Union Emissions Trading System (EU ETS) price which, in addition to CO_2, includes N_2O and perfluorocarbons (PFCs), but notably excludes HFCs. A comprehensive model accounting for carbon price risk under consideration of refrigerant price increases would be methodologically feasible analogous to e.g. Oertel et al. (2022). In addition to the absence of concrete risk indicators, real estate companies currently lack specific consumption data of refrigerants. Yet they need this data as a basis for assessing refrigerant-related carbon price risk as a transitory risk and to derive decarbonization strategies.

Overall, the following working hypotheses can be derived from the current state of research:

H1: F-gases have a statistically significant impact on the emission levels of food retail properties.

H2: The average share of F-gas emissions on total emissions in food retail properties is above the commercial real estate average of 1.8%.

The stated hypotheses are to be tested by means of an empirical study with consumption data from German retail properties. The research design outlines the concrete methodological framework for testing the developed hypotheses.

3.4 Research design

The CRREM initiative is one of the few to directly include F-gases in its tool in the calculation of the emissions inventory. Furthermore, it serves as the leading global initiative establishing targets for operational carbon emissions specifically for standing real estate investments consistent with the ambitions of the Paris agreement. In addition to the assessment of the properties' CO2e per square meter per year, this performance indicator permits benchmarking against Paris-compliant decarbonization pathways, thereby facilitating the identification of stranding risks. Consequently, CRREM is a suitable tool for examining the influence of F-gases on the emission levels of buildings.[7]

Figure 6. Structure of the CRREM tool

Source: Spanner and Wein (2020).

The design of CRREM is depicted in Figure 6 and is structured as follows: In the "input" tab, users can enter asset level data including general information, building size, vacancy rates, and energy procurement data. The data information concerning renewable energy generation, both on-site and off-site, future retrofit measures, and refrigerant losses, is optional. Energy consumption data (in kWh) can be reported in the input tab for the baseline year which will then apply to all years until 2050. Analogously, for refrigerant losses, details such as type of gas and amount of leakage (in kg) are of interest. The tool subsequently converts the input figures with its different units (kg, kWh, etc.) into a baseline carbon performance metric measured in

[7] CRREM Tool (V1) available for download via http://www.crrem.eu/tool.

the unit CO2e. The asset baseline performance is further influenced by additional factors, notably the impact of grid-decarbonization and the change in heating and cooling degree days (HDD/CDD) (Spinoni et al., 2018).[8] CRREM calculates the corrected asset baseline performance which takes into account these two effects, and hence, is not linear over time.

The asset's baseline GHG-intensity, denoted in kgCO2e/m2/yr is determined by

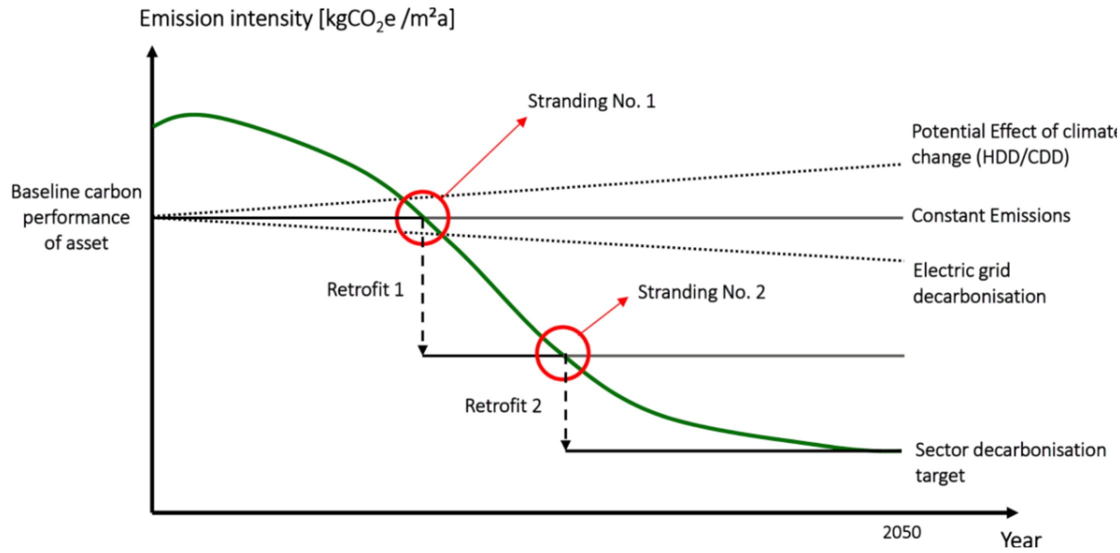
$$kgCO2e/m2/yr = \frac{E \cdot \beta}{a} + \frac{L \cdot GWP}{a} \tag{1}$$

with the first fraction signifies the indirect emissions, whereas the second representing the direct emissions. The indirect emissions are composed of the annual whole-building energy demand [kWh] E multiplied by the weighted emission factor, e.g. Energy-mix Germany β, over the property area [IPMS2] a. This is then summed with the direct emissions represented by the annual refrigerant loss [kg] L times the respective Global Warming Potential GWP, all divided by a. This calculation methodology enables the isolated analysis of the impact of the CO2 "equivalents", which can be added to the GHG-intensity, thus creating a comprehensive metric encompassing all GHGs (Hirsch et al., 2019).

Output is available both at the asset level and the portfolio level. At the asset level, the main result is the "stranding diagram" exemplified in Figure 7 below. In this illustration, the green line denotes the specific Paris-aligned decarbonization pathway (1.5°C or 2°C target). The black line represents the current and future emissions of the building, expressed in kilograms of CO2e/m2/yr. The point of intersection denotes the critical juncture of "stranding", meaning that the asset is no longer Paris-compliant.

[8] The CRREM model applies the climate model data of Spinoni et al. (2018) to the future development of HDD/CDD, to cover the effect of climate change.

Figure 7. Stranding diagram



Source: Spanner and Wein (2020).

The comprehensive analysis of the entire real estate portfolio is conducted within the "portfolio level" section. This section shows specific charts and key figures that are beneficial for reporting interactions between investors and trustees. The analysis can be performed for the entire portfolio or filtered by country, asset class, and individual funds.

Following the determination of the actual CO2 and CO2e emissions, the hypotheses are subject to confirmation or rejection. To confirm whether F-gases have a significant effect on the emission levels of food retail properties, a paired samples t-test is carried out analogous to e.g. Wiley (2012). This statistical test can be effectively applied to a smaller sample size and to correlated samples.

In detail, the test compares the mean of the CO2e emissions excluding F-gases μ_A with the mean of the CO2e emissions including F-gases μ_B. The null hypothesis of the t-test states that there is no significant difference in the means of the CO2e emissions before and after considering F-gases. In contrast, the alternative hypotheses confirm a significant difference in the means of the CO2e emissions before and after considering F-gases. The determination of any substantial difference is conducted at a significance level of $\alpha = 0.01$.

The t statistics is obtained by

$$t = \frac{\bar{x}_{diff} - 0}{s_{\bar{x}}} \tag{2}$$

where

$$s_{\bar{x}} = \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}} \tag{3}$$

In this framework $\bar{x}_{diff}$ represents the sample mean of the differences in CO2e and $s_{\bar{x}}$ signifies the estimated standard error of the mean. The latter is derived from the variances of the samples S_1^2 and S_2^2, divided by their respective number of observed assets n. The specification of (3) is especially suitable in the case of different variances of the samples (Welch, 1947). The effect size can be validated by Cohen´s (1988) d:

$$d = \frac{\bar{x}_{diff}}{\sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}} \tag{4}$$

It measures the standardized mean difference of an effect and with this the degree to which the effect of F-gas emissions on the GHG performance of food retail properties is present in the German market.

3.5 Data and descriptive statistics

In the scope of the research, a total of 29 retail properties belonging to a cooperation partner, which is anonymized for reasons of data privacy compliance, were evaluated for the baseline year 2019. The partner is a leading company in the international retail sector with nearly 500 assets in the European portfolio, thereby representing the operator side of the properties. Under consideration of the generally limited data availability in the market, this enabled to generate a comprehensive example of the retail sector in Germany.

Table 5 provides an overview of the portfolio specifics. In 2019, the properties exhibited an average age of 32 years and had an average gross floor area of approximately 11,645 m2. Collectively, the stores had an energy consumption of approximately 82 million kWh, equating to an average consumption rate of around 242 kWh/m2/yr. Moreover, the combined emissions of these properties amounted to 10,000 kg of F-gases. Renewable energy was partly generated on-site, but off-site renewable energy was not purchased. The location-based emission factors (an EF of 0.517 in 2019 and 0.175 by 2050) were used for electricity on all assets in Germany.

Table 5. Summary statistics

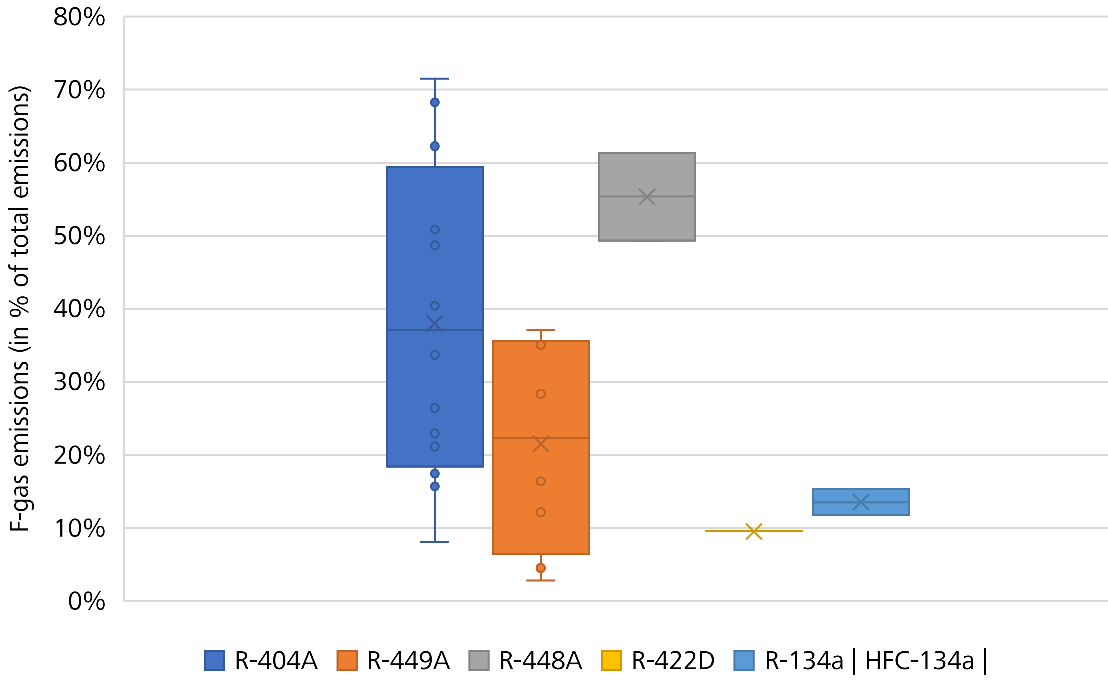
	Building age	**Gross floor area**	**Energy procurement**	**Renewable energy produced on-site**	**Fugitive emissions**
Unit	years	m2	kWh/yr	kWh/yr	kg/yr
Sum	-	337,717.00	81,748,074.00	1,576,380.00	9,765.00
Mean	32	11,645.41	2,814,763.31	525,460.00	336.70
SD	14.55	5,258.00	1,325,028.91	230,166.56	352.77
Min	11	2,219.00	550,261.24	200,000.00	11.00
Max	53	17,771.00	4,547,600.85	692,860.00	1,237.00
Med	33	13,518.48	3,202,148.75	683,520.00	143.00

Source: Authors own work.

In the following, a preliminary descriptive analysis is carried out, having employed formula (1) to compute the total emissions both without and with F-gases for each asset. The detailed asset and portfolio analysis with regard to the decarbonization pathways as well as the t-test are presented in chapter 5.

As illustrated in Figure 8, fugitive emissions make up a significant proportion of the total emissions, varying between less than 5% and as high as 72% in specific stores. The boxplots reveal mostly symmetrical patterns, albeit with considerable dispersion noted for R-404A and R-449A with a wide interquartile range. Although exhibiting a large bandwidth, all observations are within the interquartile ranges of the different refrigerant box plots reducing a potential bias due to outliers (see Appendix for a more detailed view on outliers). As most markets use R-404A we have the clearest picture for this refrigerant. It shows that its share of total emissions varies widely, with a median of 38%. R-449A demonstrates more modest fluctuations, with a median of approximately 22%. By comparison, R-448A, R-422D and R-134a exhibit minor fluctuations, although this may be due to the small sample size. Against this background, the medians between 10% and 55% are not informative. Leaving the latter observations aside, it is plausible to conclude that the refrigerant R-404A exhibits the highest median proportion of F-gas emissions in total emissions, given its notably high GWP.

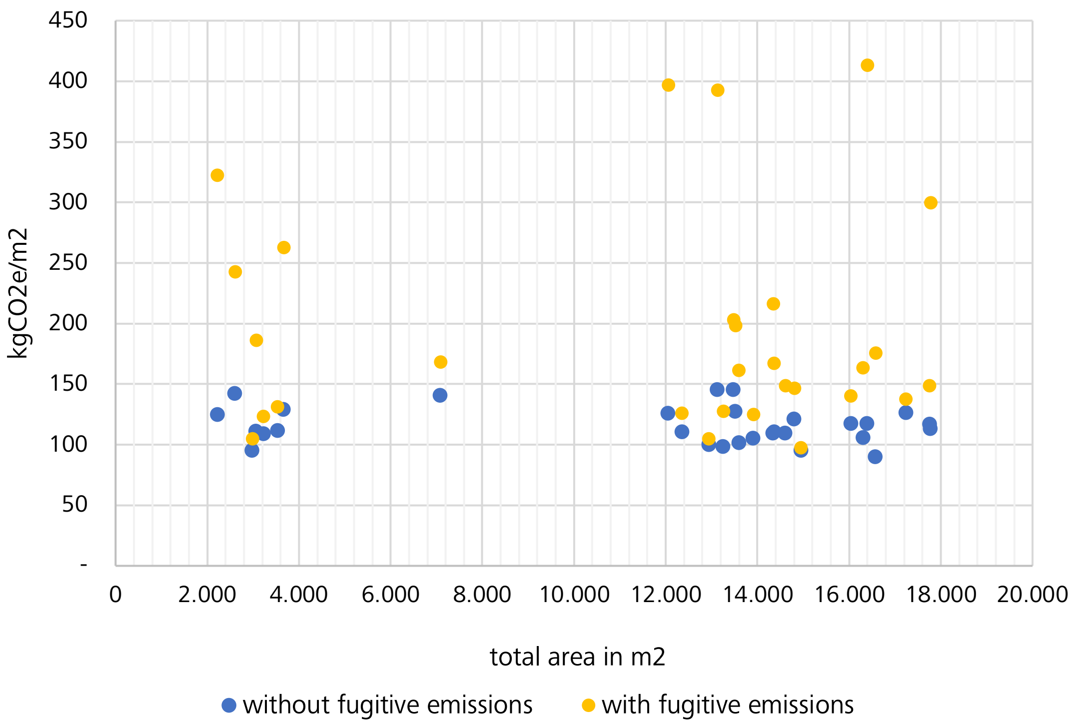
Figure 8. Share of F-gas emissions on total emissions for different refrigerants



Source: Own illustration.

Figure 9 visualizes an analysis with respect to varying store sizes, plotting the emissions without (blue) and with (yellow) F-gases per m2 for each asset, arranged in ascending order of area. The emissions per m2 without F-gases exhibit relatively consistent values across all area sizes. This is plausible, because a greater area does not necessarily equal higher electricity consumption per m2, but only in absolute terms. Conversely, one might anticipate a need for more branched refrigeration systems in larger areas, potentially leading to higher leakage rates. Furthermore, Figure 9 already shows an initial indication of the substantial impact of refrigerant losses on the total emissions of retail properties, though this consideration requires further verification. Noticeable deviations are evident, possibly influenced by factors such as the age of the equipment, efficiency, type of F-gases used, and maintenance intervals.

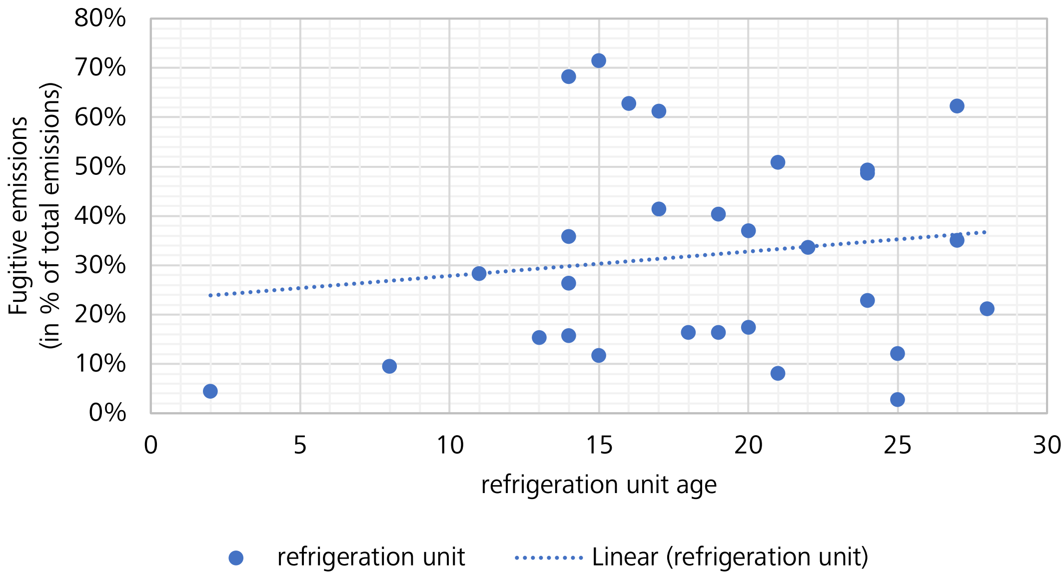
Figure 9. Total GHG emissions of portfolio properties excluding and including refrigerant losses in relation to property size



Source: Own illustration.

As noted above, the average portfolio age for all assets reporting on F-gas emissions is 32 years. In this specific portfolio, minimal to negligible correlation was detected between the two variables building age and F-gas emissions, with the correlation coefficient close to zero (Figure 10). However, it is noteworthy that refrigeration units have a depreciation period of 15 years and a maximum lifespan of approximately 20-25 years, following which they are replaced. Placing the refrigerant losses against the approximate refrigeration unit age, a marginal positive trend with a slope of 0.0049 emerges. This suggests a deterioration of the system and hence an increased leakage rate and/or a refrigerant with higher GWP.

Figure 10. F-gas emissions (in % of total GHG emissions) in relation to the refrigeration unit age



Source: Own illustration.

To conduct a paired sample t-test, the parent populations of the samples CO2e emissions excluding F-gases μ_A and CO2e emissions including F-gases μ_B are assumed to be distributed normally. The skewness of μ_A is 0.44 and its excess kurtosis is -3.68. For μ_B, a skewness of 1,20 and an excess kurtosis of -2.72 is observed. Still, the Shapiro-Wilk normality test states a normal distribution at a significance level of 0.05 for μ_B. For μ_A, a normal distribution cannot be confirmed. Nonetheless, the paired sample t-test to be performed can be considered valid since the sample size is larger than 15 (Ratcliffe, 1968). Additionally, the difference in the samples' variance is accounted for in the t-test, which is 229.37 for μ_A and 8,149.25 for μ_B.

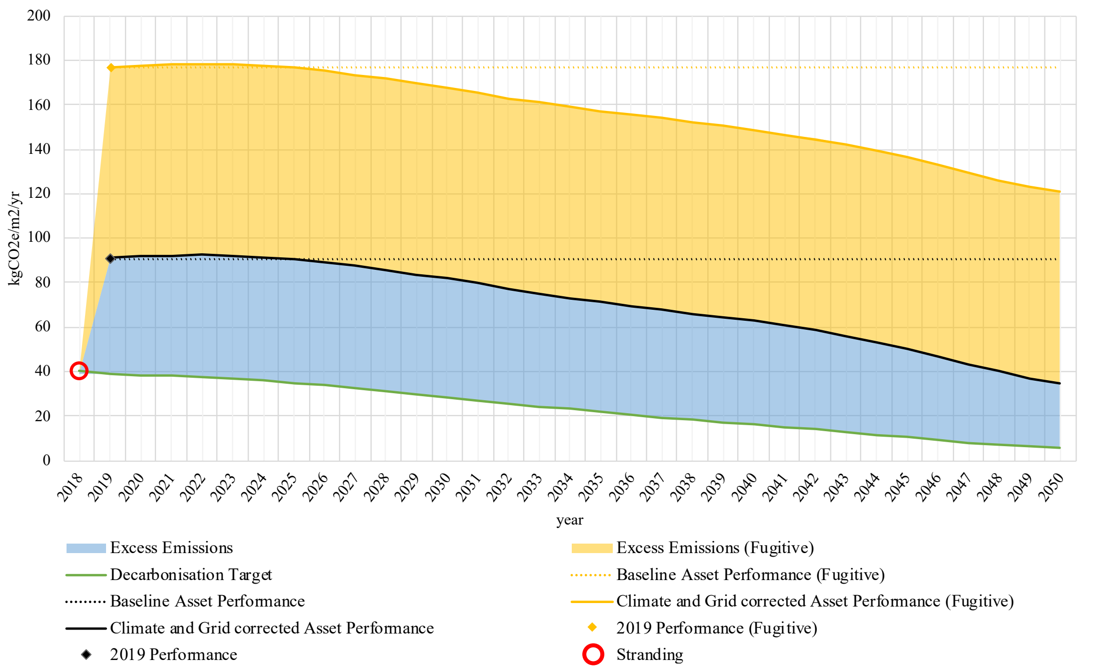
3.6 Results

3.6.1 Asset level analysis

The impact of one 16,576 m2 large asset in the portfolio is shown below in Figure 11. In this specific asset, the combined emissions of grid and gas consumption result in a total of 90 kgCO2/m2. This is number retrieved with 2,658,380 kWh multiplied by an EF of 0.517 and 676,945 kWh multiplied by an EF of 0.184 respectively. The loss of 363 kg of the refrigerant R-404A with a GWP of 3,922 contributes additional

86 kgCO2e/m2 per year. A consideration of F-gases mounts the asset-baseline GHG-intensity in 2019 from 90 kgCO2/m2 to a total of 176 kgCO2e/m2/yr. In this specific case, the F-gas emissions account for 48% of total emissions, revealing the significant impact of refrigerant losses. Furthermore, this share of F-gas emissions is well above the commercial building average benchmark of 1.8%.

Figure 11. Asset level output

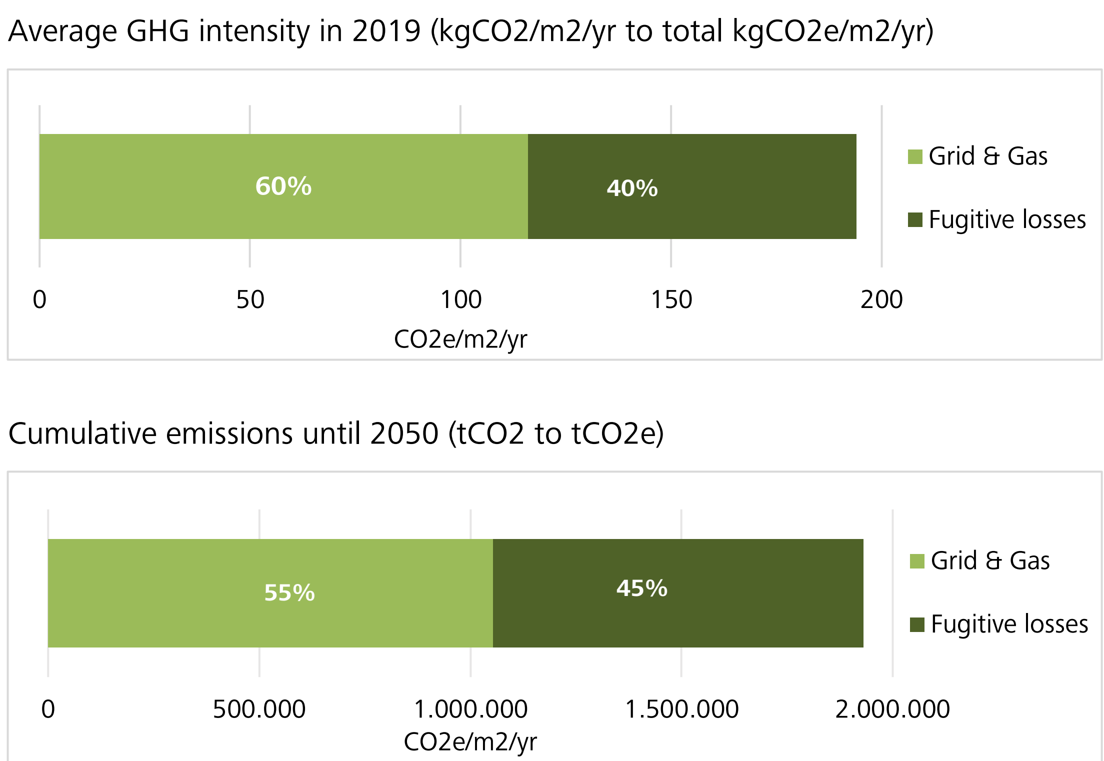


Source: Own illustration.

3.6.2 Portfolio level analysis

The results revealed significant variance in the overall performance across the portfolio. This may be attributed to building characteristics such as age, energetic refurbishments undertaken, and property-type mix. Already in the first year, the assets in the German portfolio do not comply with the threshold for the 2°C Paris-compliant target in terms of GHG intensity. Including refrigerant losses, it averages approximately 195 kgCO2e/m2/yr, ranging from 98 kgCO2e/m2/yr to 413 kgCO2e/m2/yr in the first year (with the worst performing asset using 1.237 kg R-404A per year). To be Paris-compliant by 2050, the average GHG intensity must reach zero (or at least around 5 kgCO2e/m2/yr for the 2°C target in Germany and 1.3 kgCO2e/m2/yr for the 1.5°C trajectory). Figure 12 illustrates the portfolio performance with and without refrigerant losses, highlighting a significant impact on the overall performance. On average, F-gases account for 40% of the total performance and nearly 45% of cumulative emissions until 2050. This confirms the hypothesis stating that the average share of F-gas emissions on total emissions in food retail properties is above the commercial real estate average of 1.8%.

Figure 12. Average portfolio performance on GHG excluding and including refrigerant losses



Source: Own illustration.

To prove the statistical significance of the findings we compute the paired samples t-test. The two samples are moderately positively correlated (0.52, see Table 6), which supports the paired test over an unpaired one. We test whether the null hypothesis (H0) stating that there is no significant difference in the means of the CO_2e emissions before and after considering F-gases can be rejected. The results in Table 6 show that the t-statistic is at 30 degrees of freedom approximately 4.63 with a p-value less than 0.01, and thus H0 can be rejected. This indicates that there is a definite, consequential relationship between the two occurrences and F-gases have a statistically significant impact on the emissions levels of food retail properties. Furthermore, the effect size

d is approximately 1.22, which indicates that the difference between the CO2e emissions before and after considering F-gases is equal to 122% of a standard deviation. While large effects are recommended to be greater than 0.80, the result shows a markedly large effect (Cohen, 1988). The results confirm the hypothesis that F-gases have a statistically significant impact on the emission levels of food retail properties.

Table 6. Results of the paired samples t-test

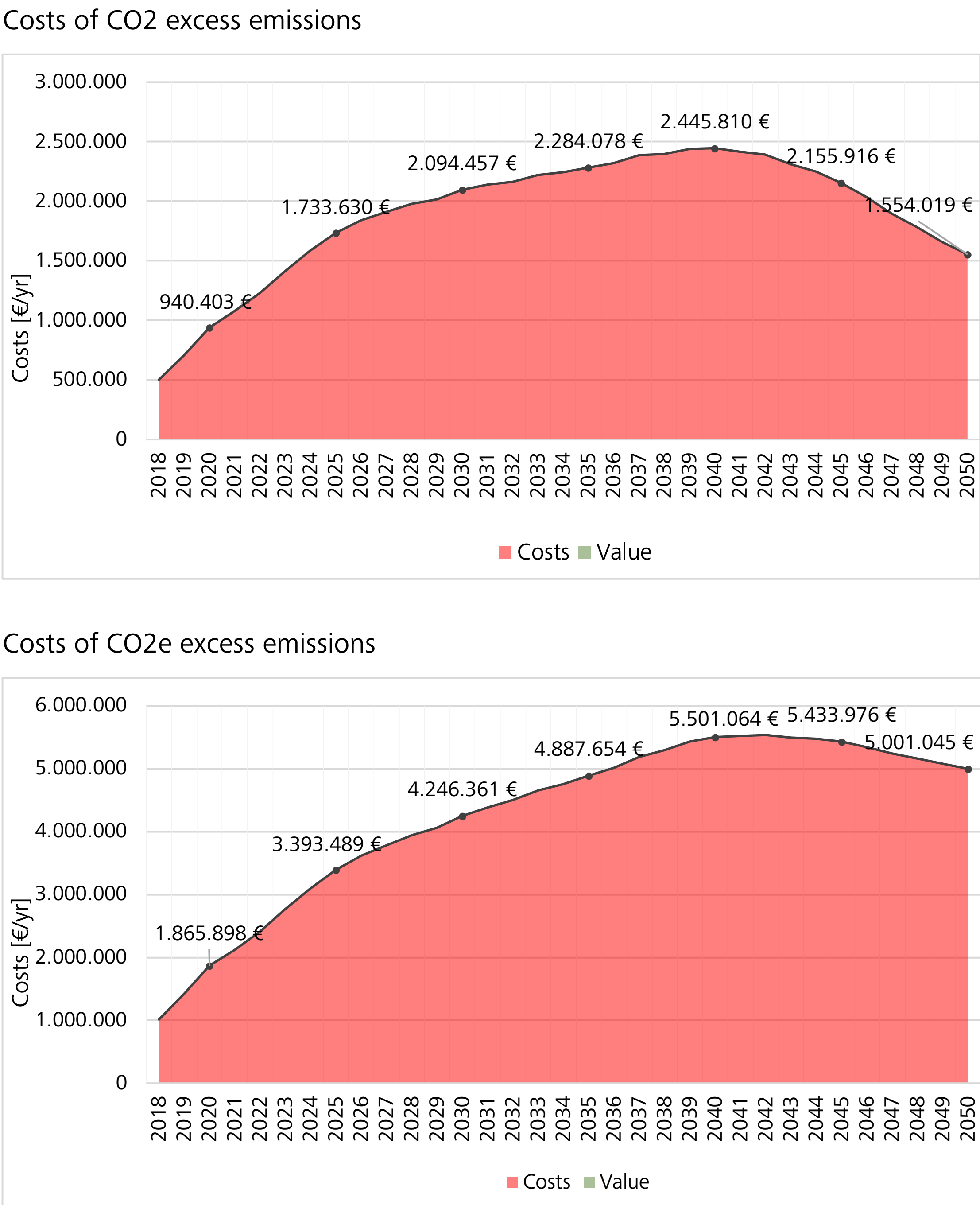
	CO2e/m2 excl. F-gas emissions	**CO2e/m2 incl. F-gas emissions**
Mean	116.0252248	194.6700354
Variance	229.3719836	8149.248477
Observations	29	29
Pearson Correlation	0.517787081	
Hypothesized Mean Difference	0	
df	29.575	
t Stat	4.6268	
p-value	0.00006866	

Source: Authors own work.

Building upon this result and recognizing the underestimated significance of F-gases, further transitory risks should be considered. One viable approach involves the quantification of an internal carbon price for asset owners, as illustrated in CRREM for all excess emissions at portfolio level. This entails applying a specific price in the unit €/tCO2e. It is composed of a direct price on emissions for electricity and gas, which increases over time, as well as the increase in electricity prices themselves. Figure 13 (top) depicts the trajectory of the carbon price for excess emissions without taking F-gases into account. As the portfolio already includes excess emissions in 2018, there is an immediate risk of additional costs. By 2040, these costs are projected to be approximately five times higher, in line with the increasing excess emissions of the portfolio, before decreasing in relative terms. The decline is due to the assumption of increasing grid decarbonization.

In addition to the pricing of CO_2 from electricity and gas as well as the indirect pricing via rising electricity costs, F-gas emissions introduce additional costs. These costs can manifest through rising refrigerant purchase prices due to the phase-down, along with the concept of pricing of excess F-gas emissions. In the current version of the tool, CRREM calculates these excess emissions using the same carbon price that is applied to electricity and gas. The outcomes concerning the pricing of portfolio emissions including F-gases are shown in Figure 13 (bottom). When taking the costs for the "equivalents" into account, it results in a twofold increase in the first year and a rise of over 200% by 2050. The decreasing costs towards the end of the observation period, attributed to the decarbonization of the electricity grid, are also visible here. However, it is apparent that the lower the share of electricity and gas in total emissions, the less pronounced this effect.

Figure 13. Forecast of the cost components in terms of CO2 costs compared to CO2e costs



Source: Own illustration.

In summary, investors should prioritize investing into green alternatives over paying a CO2 price. Relying solely on the energy system for decarbonization will likely be insufficient for most real estate assets to achieve net-zero emissions by 2050. Even after grid decarbonization, the responsibility for minimizing direct emissions from refrigerants remains with the user and owner of the building. Companies seeking best-practices are hence increasing their ambition levels by implementing a "Zero Emissions Target for Refrigerants" or adopting a robust and transparent "F-gas Exit Program". Examples may include, but are not limited to:

- monitoring and benchmarking leakage rates,
- implementing intelligent repair solutions (with smaller exchanges such as propene plug-ins),
- removal of open cooling shelves in stores,
- emphasis on trans-critical (TC) technology with ejector and heat recovery systems,
- development and installation of digital logbooks for cooling systems as software applications for increased transparency and monitoring.

3.7 Conclusion and outlook

The global warming potential associated with refrigerant losses remains significantly underestimated within the real estate sector. This oversight is compounded by one of the sector's biggest challenges: the reduction of GHG emissions resulting from the ongoing poor energy efficiency of existing buildings and remaining low refurbishment rates across virtually all countries. Climate change poses a fundamental threat to economic growth, quality of life, political stability, and increased exposure to a value discount due to stricter standards (Brounen et al., 2020). Research also underlines that portfolios exhibit a significant relationship between their operating performance and "greenness" (Ooi et al., 2019). The planet has already warmed >1˚C since pre-industrial times and studies indicate that a further 3-4°C rise in temperatures seems highly likely (IPCC, 2020). The real estate sector must support global climate goals by setting net-zero targets. For these targets to be effective, data transparency, appropriate metrics, and management support are critical. CRREM provides a solution to the challenges faced by the property sector to align with the Paris targets and mitigate transition risks. However, benchmarking against the CRREM Paris-aligned targets is often done without considering other GHGs (CO2e). This leads to inconsistencies in the "whole-building" approach taken. Furthermore, the underestimation of the GWP of refrigerant losses persists due to limited research attention. This leads to an enduring lack of information on availability and transparency, as well as inconsistent measurements and risk analysis.

Refrigerant losses represent an important source of harmful GHG emissions from buildings, particularly for retail assets. Nevertheless, other property types, such as hotels or offices, should not be neglected, as these also feature large cooling units – especially in warmer climates. Measuring these F-gas emissions and transitioning to environmentally friendly technology is therefore essential. Additionally, a clear comparison and differentiation between the wording "CO2" and "CO2e" for controlling and reporting is important, especially for commercial properties. Currently, there are limited concrete obligations on the part of policy makers, apart from the phase-out of certain refrigerants.

The study has revealed that refrigerants impose a significant impact in terms of the total carbon intensity of properties. In some cases, the stranding risk is considerably greater than expected, showing that F-gas emissions amount to a significant proportion of the total emissions. We can confirm the hypothesis stating that F-gases have a statistically significant impact on the emission levels of food retail properties additionally with a paired samples t-test. The results demonstrate that, on average, F-gas emissions account for 40% of the total performance and nearly 45% of cumulative emissions until 2050. The second hypothesis is similarly affirmed, as the average share of F-gas emissions on total emissions in food retail properties is well above the commercial real estate average of 1.8%. It should be noted that while these results are insightful, their application to all existing food retail properties in Germany in Europe is limited due to the small sample size and the wide variation of F-gas shares among individual properties. Nevertheless, the resulting average share clearly surpasses the commercial real estate average and underlines the importance of food retail properties. Furthermore, given the increasing cooling degree days in many parts of Europe, signifying a growing number of days when buildings require cooling, an intensive examination of the topic becomes imperative.

The future pricing of emissions from refrigerants remains uncertain. As described in the literature review, the EU ETS so far includes N2O and PFCs in addition to CO2, but not HFCs. A more reliable risk assessment could involve directly factoring rising refrigerant prices, similar to the consideration of rising electricity prices. However, forecasting fluctuations in refrigerant prices remains challenging at present. Since the introduction of the EU phase-down, the average HFC surcharge for the period between 2015 and 2019 has been 8 €/tCO2e for manufacturer purchase prices and 16 €/tCO2e for prices via intermediaries (Birchby et al., 2022). To our knowledge, there are no concrete publicly available figures on future price developments. From an academic perspective, we particularly encourage a prediction of refrigerant prices and a related accurate calculation of carbon risk for specific properties. Based on this, it would be worth considering whether including these costs or risks in MAC curves, as in Hart et al. (2020), would develop in favor of refrigeration systems using alternative refrigerants. Moreover, if in the future more refrigerant consumption data becomes available, a regression model with refrigerant consumption and corresponding CO2e emissions as dependent variable on explanatory variables such as construction year of the building, construction year of the refrigeration system, location and size of the building, type of refrigerant and type of user, would also be possible and highly relevant to identify the crucial determinants of high CO2e emissions. An inclusion of transaction prices or rents as endogenous variables would provide important implications for the investment market in the form of estimated green premiums or brown discounts.

From a property owner's point of view, we encourage the collection of consumption data of refrigerant losses and the integration into the CO2e monitoring processes of real estate companies. For tenants digital monitoring through logbooks for the cooling systems may offer an efficient initial solution. Additionally, continuous assessments of MAC curves should be conducted to determine the economic feasibility of converting or replacing systems with alternative refrigerants.

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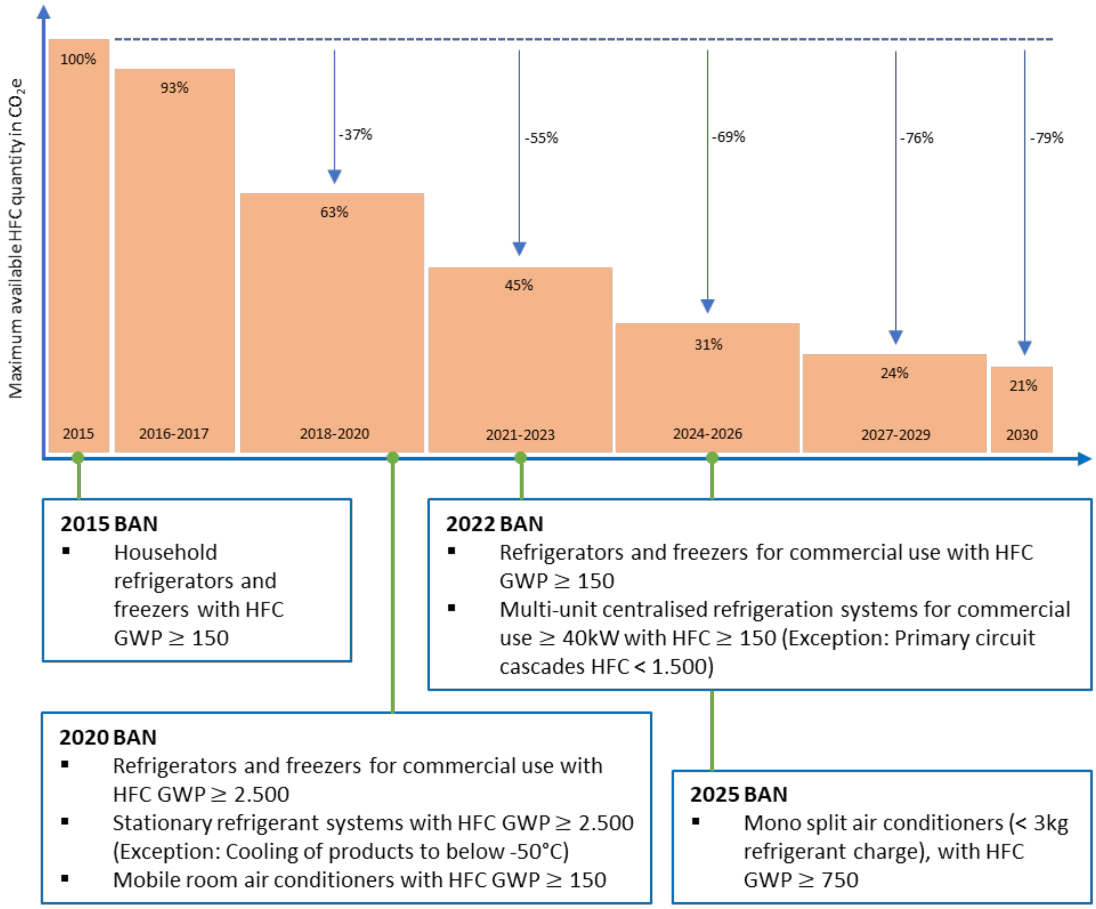
3.9 Appendix

This Appendix presents supplementary information on the EU F-gas regulation. Furthermore, it provides deeper insight on potential outliers in the analyzed data set as well as on the calculation of the TEWI as indicated by Islam et al. (2017).

EU F-gas regulation of 2014

Figure 14 illustrates the detailed phase-down schedule outlined in the EU F-gas regulation of 2014. In addition to the limitation of the production volume of HFCs, various usage bans will be in effect until 2025.

Figure 14. EU F-gas regulation of 2014

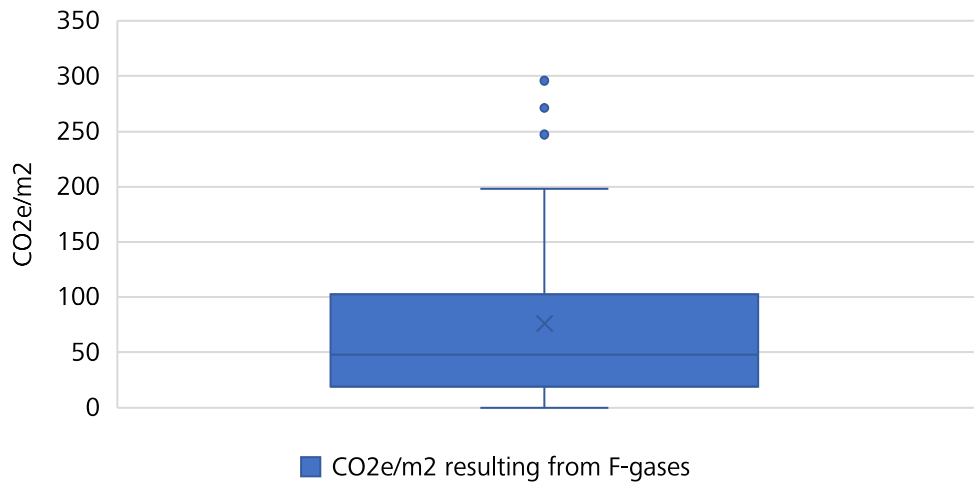


Source: Author representation based on Regulation [EU] No 517/2014 (2014).

Analysis on outliers in the sample

While the relative F-gas share on total emissions does not exhibit concerning outliers (see Figure 8), there are three outliers observed in the sample concerning the absolute additional emissions caused by F-gases (as depicted in the box plot in Figure 15). Nevertheless, performing the paired t-test with the adjusted sample size yields results consistent with those obtained from the original sample, as presented in Table 7. The t-statistic, with 25 degrees of freedom, approximates 5.46, yielding a p-value less than 0.01. Consequently, the null hypothesis can be rejected.

Figure 15. Total F-gas emissions per m2 of the observations



Source: Own illustration.

Table 7. Results of the paired samples t-test with smaller sample adjusted for outliers

	CO2e/m2 excl. F-gas emissions	**CO2e/m2 incl. F-gas emissions**
Mean	114.4221	170.8298
Variance	214.6508	3403.363
Observations	26	26
Pearson Correlation	0.4906022	
Hypothesized Mean Difference	0	
df	25	
t Stat	5.4557	
p-value	0.00001152	

Source: Authors own work.

Calculation example – Carrier 30XW 880, illustrating the low influence of F-gases at this shopping center refrigeration system

This calculation example is intended to show that refrigerants should be considered in combination with electricity consumption. In addition to simultaneously increasing resilience through higher security of supply, for example, it is essential to improve asset electricity performance through more on-site production. In this case the TEWI-Ratio is smaller than one, indicating a low influence of F-gases at this shopping center.

GWP = 1,430 (for R-134A)

L = 175 kg total filling · 1.3% leakage rate = 2,275 kg

E = 246,000 kWh

β = 0.35 (energy-mix Germany)

$$direct\ emissions = 2.275 \cdot 1.3\% = 3{,}253.25\ kgCO2e/\mathrm{yr}$$

$$indirect\ emissions = 246{,}000 \cdot 0.35 = 86{,}100\ kgCO2e/yr$$

$$TEWI = 3{,}253.25\ kgCO2e/yr + 86{,}100\ kgCO2e/yr = 89{,}353.25\ kgCO2e/yr$$

$$TEWI - Ratio = \frac{3{,}253.25\ kgCO2e/yr}{86{,}100\ kgCO2e/yr} = 0.04$$

4. Do Retail Property Markets in Singapore Ignore Flood Risk as a Natural Hazard?

4.1 Abstract

Natural hazards pose significant risks for buildings and, as such, investors and their property portfolios. Aside of rising sea levels as one consequence of climate change, one of the most significant sources in this context are extreme weather events, especially flood events from heavy rain and related externalities such as landslides. This study aims to analyze whether retail property markets in Singapore consider flood risk in inherent pricing mechanisms. We identify properties within distinct flood-prone areas and include several control variables from property price models to account for hedonic pricing characteristics. Based on 6,322 address-level observations of transaction prices in Singapore, we estimate an OLS as well as a Generalized Additive Model with geospatial components to account for the pricing mechanisms. We identify a statistically significant price discount of 13.5% c.p. on average from flood risk within the defined flood-prone area. Furthermore, the model delivers insights into market dynamics and the impact of low or high energy efficiency on pricing in retail properties. We conclude that, while Singapore has implemented several measures in terms of flood risk management, the retail property market still accounts for potential damages or inconveniences from flood events with a measurable discount on transaction prices.

Keywords – retail property; Singapore; natural hazard; flood risk

4.2 Introduction

Asia's metropolises are highly affected by rising sea levels as well as the immanent risk of flood events. Estimates of Wang and Kim (2021) quantify the expected impact of changing sea levels and 10-year floodings on respective GDPs as well as the number of people at risk to be quite significant in urban areas such as Tokyo (830,000 people affected, -7% GDP), Jakarta (1.8m people affected, -18% GDP), or, worse, Manila (1.54m people affected, -87% GDP), and Bangkok (10.45m people affected, -96% GDP). As a coastal city, Singapore has been subject to increased vulnerability from rising sea levels and the immanent risk of flooding as well, which has worsened due to climate change. Despite improving flood risk management in the city, Singapore has experienced flood events almost every year since 2008, mainly arising from heavy rainfall in magnitudes of up to 153mm within three hours (Chan et al., 2018).

In their newest Synthesis Report on behalf of the IPCC, Lee et al. (2023) determine with high confidence that human-induced climate change affects weather and climate extremes globally with losses and damages to nature and people. Moreover, they expect that, going forward, the increase of sea levels as well as the occurrence of extreme weather events such as floods will most likely continue to happen more frequently, more intensively, as well as with higher (financial and social) damage to ecosystems, infrastructure, and livelihoods. Moreover, they establish that certain regions are likely to be more affected than others.

In this context, Singapore as a low-lying island in the tropics can be considered a high-risk region. The National Climate Change Secretariat (NCCS) of Singapore estimates that sea levels around Singapore are projected to rise by one meter until 2100. Around 30% of its land are less than five meters above sea level and significant land reclamation has been initiated to mitigate this risk by 2100 as far as possible (NCCS, 2023). In addition, Singapore has been subject rising rainfall intensities and an increasing frequency of intense storms. About 30.5 ha were considered as flood prone areas in 2016. Adaption measures towards this part of climate change comprise mainly the field of local food supply, as well as drainage management (Koh, 2023). The latter is part of infrastructural measures to protect the population as well as dwellings and commercial buildings.

Given the potential damage from extreme weather events, rational investors would intend to price in the discounted effects from expected long-term damages into their investment activities. Specifically, one would expect lower acquisition prices in light of future losses in asset value or from loss of rent due to temporary or permanent non-usability. This paper aims at testing this hypothesis. More extensively, we analyze and discuss questions, such as:

1. Do markets account for the risk of sustaining property and financial losses in terms of their pricing mechanisms?
2. To what extent are these risks represented in transaction prices empirically?

3. Are these effects invariable over time, especially without any impact on market dynamics after flood events?

For question (3), we consider the four extreme weather events in Table 8 to be potential triggering events for the event study.

Table 8. Significant hydrological extreme weather events in Singapore since 2008

Date	**Core location**	**Peak rainfall**	**Property damage**
19 November 2009	Bukit Timah Canal (overflow)	110 mm total 92mm/0.5hs	n/a
16 June 2010	Orchard Road	More than 100mm/2hs	Significant (destructions mainly in food courts and shops)
23 December 2011	Orchard Road	152.8mm/3hs	Significant (destruction from flood water accumulated in shops)
5 September 2013	Western Singapore	n/a	n/a

Source: Government of Singapore (2023).

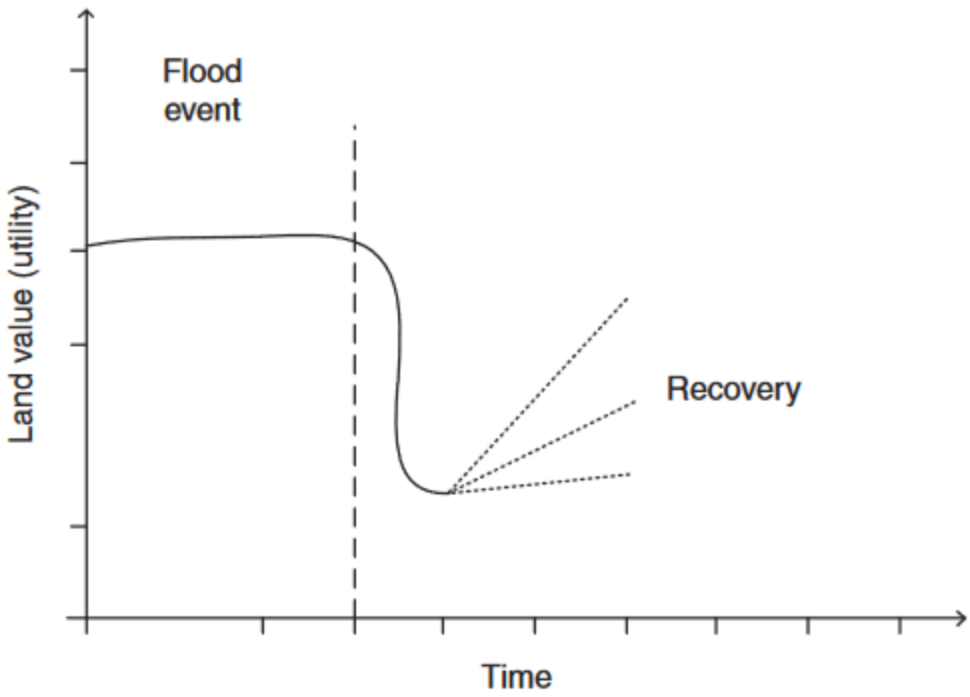
The rest of this paper is structured as follows: First, we provide an extensive review of existing literature to summarize theoretical foundations as well as empirical insights in the field of hydrological risks and property markets. Chapter 3 presents the underlying data of the empirical study and explains the methodology used. In chapter 4, we outline the results of the empirical analysis and discuss them in the context of findings from the literature as well as urban developments in Singapore, such as flood risk management measures. Chapter 5 concludes the paper with a summary and the identification of further fields of research as well as a reflection on the limitations of the study.

4.3 Literature review

Given the global importance of hydrological risks as well as the global value at risk in terms of infrastructure and properties, the volume of empirical analysis on the effect of hydrological risks on property prices is still relatively limited. However, there is substantial theory, which awaits empirical validation at a greater scale.

Tobin and Newton (1986) developed a conceptional framework for estimating the values of urban properties ex-post of a flood event. A major finding of the paper is the so-called "bounce back" effect, which describes the recovery of prices after having dropped suddenly following a flood event. The price decline is the cause of costs and damages that arise and awareness in that respect. This idea is shown in Figure 16.

Figure 16. Bounce-back effect after flood events

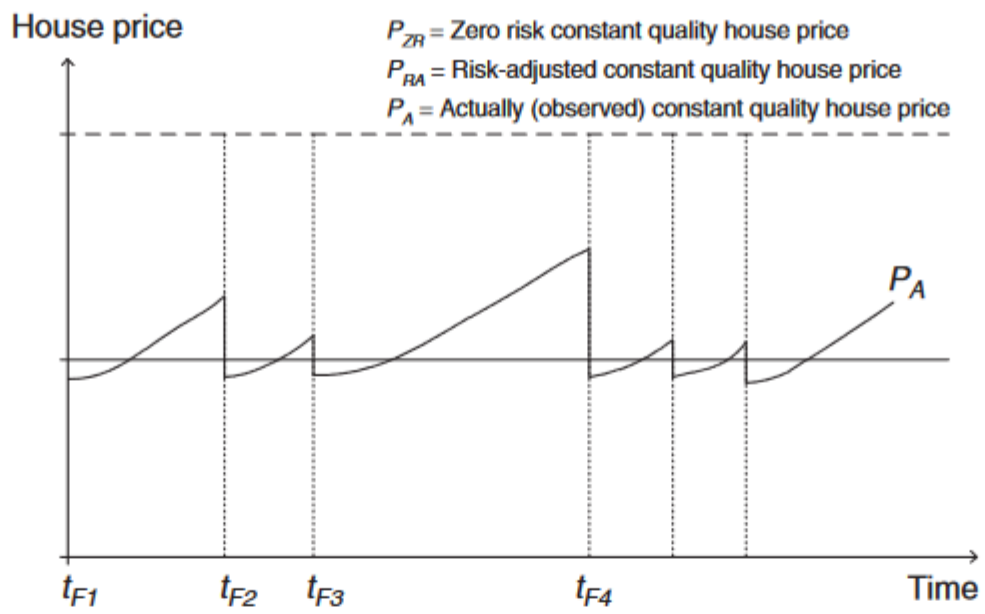


Source: Own illustration based on Tobin and Newton (1986).

In addition to the "amnesia" of the market in terms of the flood risk, prices may even exceed the value before the occurrence of the flood event, for instance due to recovery work that is potentially combined with improvements in the building quality or infrastructure. However, Tobin and Newton (1986) did not underpin their theory with actual property price information. Nevertheless, their theory seems ascertained today.

Pryce et al. (2011) built upon this fundamental idea and broadened it towards recurring events in which price recoveries are estimated to be more moderate in shorter periods between two events, and higher if there is a longer time span between two flood events, as illustrated in Figure 17. The authors add to the body of theory on market shortcomings by adding “myopia” as a terminology, describing the observation that the market inherently overweighs recent events in comparison to previous ones, even if the latter had been more severe. They conclude that risks are overestimated in the short term, while underestimated or even forgotten in the longer term. This effect seems to be more distinct once external buyers are active in the market due to related information asymmetries.

Figure 17. Myopia effects of property markets



Source: Own illustration based on Pryce et al. (2011).

Hirsch et al. (2015) added to the fundamentals of flood risk research in a real estate context by developing a methodology for estimating the damage rate and expected annual losses in property value resulting from several extreme weather events including floods. The model incorporates risk and hazard data such as climatic developments, regional vulnerability, as well as a broad capitalization mechanism for estimating property values, thereby delivering fundamental considerations to this empirical study.

In addition to and mostly in accordance with the theoretical elaborations outlined before, several papers have analyzed the impact of flood risks on property values and rents via empirical econometric analysis. These studies typically cover certain regional delimitations and local markets, local flood risk situations, and local risk management frameworks. Thus, the insights of these papers are usually barely generalizable or transferable into other individual regions.

Harrison et al. (2001), for instance, analyze approximately 30,000 property transactions in Alachua County, Florida, between 1980 and 1997. They confirm a negative impact on property values if the respective asset is located within the risk zone of a once-in-100-years flood event. At the same time, they estimate that the impact on property values seems to be lower than the price of adequate insurance. In an event-driven analysis, Bin and Polasky (2004) investigate the impact of Hurricane Floyd on property prices in Pitt County, North Carolina in 1999. Data from more than 8,000 single-family units between 1992 and 2002 shows that property values in the flood-prone area decreased significantly after the hurricane event. The same study outlines that the decrease in prices is higher than capitalized insurance costs after Floyd, but lower than before the event. Studies of Speyrer and Ragas (1991) on Greater New Orleans and Bin et al. (2008) on New Hanover County, North Carolina, point in a similar direction. The impact of Hurricane Sandy on pricing mechanisms of commercial real estate in New York and Boston in 2012 is examined by Addoum et al. (2023). They find negative price effects of flood risk exposure within a certain proximity to the coast after the event – even in coastal areas unaffected by Sandy. Furthermore, the price discount persists at a stable level in New York for the following years and at a declining level in Boston, providing limited evidence on the "bounce back" theory. Daniel et al. (2009) published a meta study on several US studies on the implicit pricing of flood risk and derive the estimation that a 0.01 increase in probability of flood risk within one year could entail a negative difference in transaction prices of (minus) 0.6 percent. Actual flood events were observed to change ex-post prices to a rather moderate extent. Also, the study postulates that there might be a biasing influence of so-called amenity effects in locations close to water, i.e. a higher willingness to pay due to the natural quality of these locations.

As one of the few empirical studies outside anglophone countries and as the first study covering a Central-European market, Hirsch and Hahn (2018) quantify estimations on the impact of a one-in-100-years flood risk on residential property rents and property values in a local German market. The analysis constructs hedonic house price models and incorporates 16,500 observations, finding a highly significant impact of flood risk on both sales prices as well as, to a lesser extent, housing rents.

Other international studies following comprised theoretical work and/or empirical analysis are on Kerala/India (Binoy et al., 2020), New South Wales/Australia (Rolfe et al., 2020), or the United Kingdom (Thompson et al., 2023). All of these studies generally point towards the finding that flood risk can, in general, be a significant market determinant, but that the extent of the impact is subject to several, mainly local, circumstances, such as the existence of flood risk management. However, the indicated literature still lacks findings on both retail property markets as well as several global regions, such as Southeast Asia. In light of this research gap, we address the following hypotheses:

H1: The purchase price of retail properties in Singapore, which are located in a flood prone area, is lower as the market incorporates the risk of damage and financial losses.

H2: The impact of flood risk on the purchase price varies over time due to specific flood events.

The stated hypotheses are analyzed by applying the data and methodology described in the following section. Subsequently, the results of the empirical analysis on the retail property market in Singapore are presented.

4.4 Data and methodology

4.4.1 Sample description

We base our study on a data set of 6,322 address-level observations of retail property purchase prices from 1995 to 2022. All prices are given in Singapore Dollar (1 USD = 1.33 SGD, as per July 22, 2023) and depict actual transaction prices. The data was extracted from the Real Estate Information System (REALIS) of the Singapore Urban Redevelopment Authority (URA). Table 9 shows the sample distribution of the individual transactions. Approximately 7,027,894 sq.ft. were sold within the observation period, with a representative range of 66 to 562 transactions per year.

Containing repeated sales, the dataset covers approximately 370 retail units of different sizes in a total of 80 shopping malls. On average, every retail unit was, therefore, sold 0.63 times per year, a comparably high number which can be explained by the fact that many transactions were completed among retailers and not always capital investors with longer investment horizons. The sale of individual retail units within the shopping malls refers to their "strata" status, which is somewhat comparable to part-ownership within the shopping-agglomeration.[9]

Table 9. Sample distribution

Year	No. of transactions	%	Total space sold (sq.ft.)	%
1995	248	3.92%	139,186.02	1.98%
1996	323	5.11%	150,201.92	2.14%
1997	219	3.46%	102,890.93	1.46%
1998	199	3.15%	107,426.80	1.53%
1999	276	4.37%	188,167.57	2.68%
2000	232	3.67%	170,684.75	2.43%
2001	191	3.02%	595,717.51	8.48%
2002	204	3.23%	129,824.63	1.85%
2003	267	4.22%	197,610.87	2.81%
2004	286	4.52%	178,467.08	2.54%
2005	231	3.65%	556,001.46	7.91%
2006	253	4.00%	159,404.10	2.27%
2007	363	5.74%	342,747.25	4.88%
2008	126	1.99%	69,072.51	0.98%
2009	198	3.13%	95,509.00	1.36%
2010	262	4.14%	511,806.57	7.28%
2011	315	4.98%	152,838.10	2.17%
2012	562	8.89%	223,255.93	3.18%
2013	533	8.43%	437,494.06	6.23%
2014	238	3.76%	87,6947.96	12.48%
2015	106	1.68%	73,442.76	1.05%
2016	70	1.11%	53,303.32	0.76%
2017	119	1.88%	789,528.61	11.23%
2018	123	1.95%	156,912.16	2.23%
2019	123	1.95%	151,529.09	2.16%
2020	66	1.04%	161,879.84	2.30%
2021	118	1.87%	219,079.69	3.12%
2022	71	1.12%	36,963.59	0.53%
	6,322	**100.00%**	**7,027,894.08**	**100.00%**

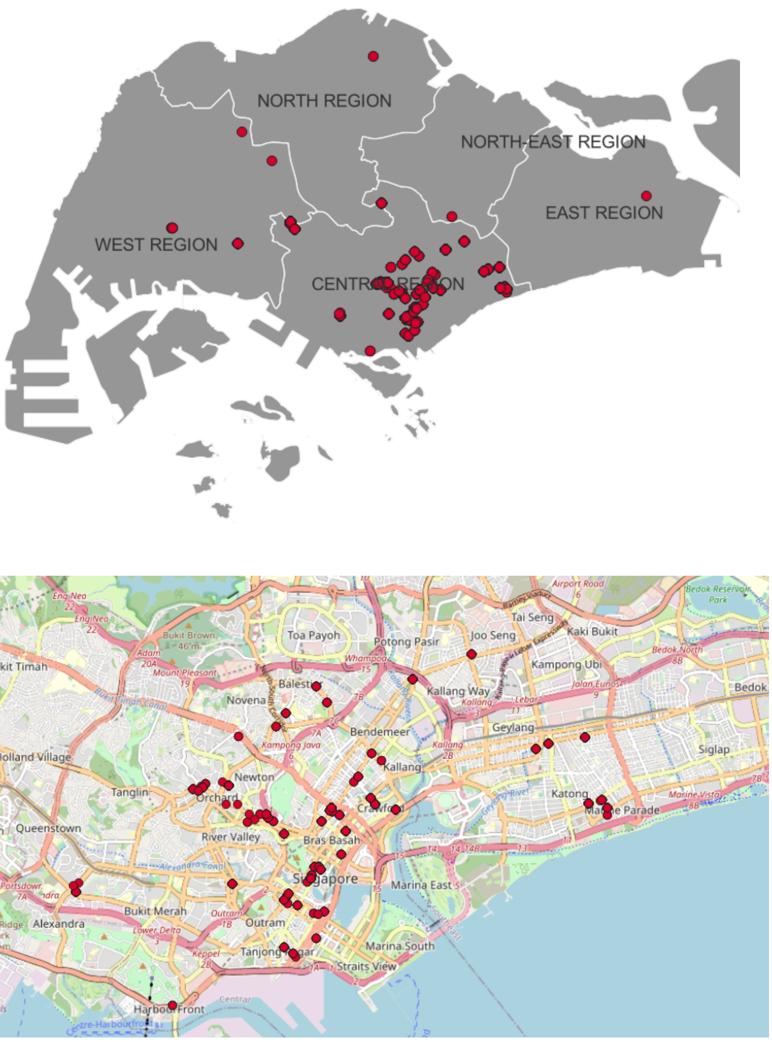
Source: Authors own work.

[9] Sub-dividing shopping malls and offices into strata-titled units was a development strategy due to lacking capital resources being a relatively young country.

The data set contains several explanatory and potentially price-determining variables, i.e. hedonic attributes such as the size/area, the story of the retail unit, and address. The properties are located all over the five regions of Singapore whereas a focus is apparent on the Central Region (see Figure 18).

Figure 18. Spatial distribution of observations

Region	No. of observations
Central Region	6,022
East Region	2
North East Region	157
North Region	2
West Region	139



Source: Own illustration with geo data of OpenStreetmap.

After intensive data exploration, we enriched the data set with additional private as well as publicly available information on the respective properties, including:

- Flood Risk Zones as per FM Global (2023),
- Energy Performance[10] from the Building and Construction Authority's Building Energy Submission System (BESS),
- Precise Geospatial Locations, measured by longitude and latitude of the property,
- Distance measures to the next public transport facility (MRT[11]).

4.4.2 Methodology

The basis of our estimation is a traditional Ordinary Least Squares (OLS) regression model, which estimates a linear relationship between the transaction price of the sold retail unit per sq.ft. (PRICE_PER_SQFT) and the target variable FLOODRISK specific to the respective location of the retail property in terms of whether or not it is located within the flood-prone area of Singapore according to FM Global (2023), or within 400 meters to that particular zone. A location within the flood prone area suggests that the particular retail property may be subject to severe extreme weather events, specifically a 100-year or 500-year flooding. We include several control variables such as the location of a unit on the ground floor (GROUNDFLOOR), the energy intensity of the shopping mall (AVG_ENERGY), the size of the individual unit sold (AREA_SQFT), and the distance to the closest MRT station (DISTANCE_MRT). To control for fixed effects a quarterly time index (TIME_INDEX) as well as the latitude (LAT) and longitude (LONG) of the shopping malls are added (see Table 10 for an overview of variables). Hence, the model is of the following form:

$$\begin{aligned} PRICE\_PER\_SQFT_{i,s,t} \\ &= \beta_0 + \beta_1 FLOODRISK_s + \beta_2 GROUNDFLOOR_i \\ &+ \beta_3 AVG\_ENERGY_s + \beta_4 AREA\_SQFT_i + \beta_5 DISTANCE\_MRT_s \\ &+ \beta_6 TIME\_INDEX_t + \beta_7 LAT_s + \beta_8 LONG_s + \varepsilon_{i,t} \end{aligned} \tag{1}$$

[10] Total electricity used within a building in a year per kWh per gross floor area in sqm.
[11] Mass Rapid Transit (MRT) is the most popular form of transportation in Singapore aside from taxis.

where i is the individual unit sold, s is the shopping center where the retail united is located, and t is the transaction date.

We further extend the OLS model to account for possible non-linear relationships by constructing a Generalized Additive Model (GAM) with Geospatial Components. While GAMs feature the general clearness of OLS models, they do not follow the assumption of linearity in the effects of variables on prices, but instead allow for smooth functions describing the relations and aim to increase the explanatory power. Our GAM follows the fundamental form:

$$Y = f_0 + \sum_{j=1}^{p} f_j(X_j) + \varepsilon \tag{2}$$

where the errors ε are independent of X_j, $E(\varepsilon) = 0$ and $Var(\varepsilon) = \sigma^2$ and f_j describes univariate smooth functions, one for each variable included in order to account for possible non-linearity. A disadvantage of GAMs is that the impact of the estimated smooth terms on the dependent variable is difficult to interpret numerically. Since we aim to estimate and interpret the c.p. effect of flood risk, this variable is included as a linear term. Control variables where there might be a high likelihood of non-linearity in the correlation, e.g. LAT and LONG, are structured as smooth terms. Consequently, we estimate:

$$\begin{aligned} PRICE\_PER\_SQFT_{i,s,t} \\ = \beta_0 + \beta_1 FLOODRISK_s + \beta_2 GROUNDFLOOR_i \\ + \beta_3 AVG\_ENERGY_s + f_1(AREA\_SQFT_i) \\ + f_2(DISTANCE\_MRT_s) + f_3(TIME\_INDEX_t) \\ + f_4(LAT_s, LONG_s) + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Ex ante, we assume that flood risk might be a significant determinant for retail property prices. Just like any other real estate segment, retail properties are subject to significant costs of repair in case of hazardous damage from extreme weather events. What is more, insurance premiums might be increasing as a result of the hazard. In addition, retail shops are, other than office and residential spaces, often located on the ground level, which is highly impacted by flood events. The hazard might lead to closures of shops – temporary or permanent – breaks, or stop of consumption, or even potential vacancy due to the departure of tenants.

Table 10. Description of variables applied in the OLS and GAM

Variable	Description	Proxy for	Remark
PRICE_PER_SQFT	Transaction price of the unit sold per sq.ft.	-	Dependent
FLOODRISK	Dummy: the property is in a flood prone area or within a proximity of 400 meters (=1) or otherwise (=0)	Risk of damage to the property and financial losses	Target
GROUNDFLOOR	Dummy: the retail unit is located on the ground floor (=1) or otherwise (=0)	Possible differences in visibility, frequency of passersby as well as turnover and profitability, but also for potentially different exposure towards damages from flooding	Control
AVG_ENERGY	Energy intensity of the property, measured by the average of energy intensities 2017 to 2020	Construction quality, status of maintenance and building age	Control
AREA_SQFT	Total size/area of the unit sold in sq.ft.	Possible differences in visibility, number, and variety of products in the shop	Control
DISTANCE_MRT	Distance to the next public transport station (MRT) in meters	Accessibility of the unit and convenience.	Control
TIME_INDEX	The quarter of price information	Market movements and the impact of timing in market transactions	Fixed Effects
LAT	Latitude/coordinate of the respective property	Other individual characteristics due to property location	Fixed Effects
LONG	Longitude/coordinate of the respective property	Other individual characteristics due to property location	Fixed Effects

Source: Authors own work.

4.4.3 Descriptive statistics and diagnostics

The summary statistics of the overall dataset is reported in Table 11. The transaction prices varied between 30.00 and 32,516.00 SGD/sq.ft. over time, with an average of 2,273.54 SGD/sq.ft. The flood risk dummy, our target variable, has a mean of 0.25, indicating that a quarter of all sold properties were located within a flood-prone area. Furthermore, 38% of all sold spaces are found on the ground floor of the shopping malls. The energy intensity is, on average, at approx. 240 kWh/m2/yr but ranges widely from 69.45 to 629.08 240 kWh/m2/yr. Since the sold spaces are strata-titled properties, the dataset exhibits shop spaces from as low as 10.76 sq.ft. up to 748,054.94 sq.ft. and an average size of 1,111.66 sq.ft. The shopping malls in which the sold shops are located have varying degrees of accessibility to public transport in the form of the MRT. While some malls are located directly next to an MRT station (9.57 m), others are difficult to reach (7,187.98 m). On average, the shops are about 395.73 meters away from the MRT station. In addition to the descriptive statistics, the correlation between covariates were analyzed to detect any multicollinearity problems in the model (see Table 12). We do not find any correlation greater than the threshold of 0.25 among the exogenous variables or 0.32 including latitude and longitude. The negative correlation of the flood risk and transaction price variables provides a first indication for a negative c.p. effect in the OLS and GAM results. The residuals in the OLS models exhibited heteroscedasticity problems, so robust standard errors were used. The GAM models did not show any abnormalities with respect to heteroscedasticity on graphic inspection (see Appendix).

Table 11. Summary statistics

	Unit	Mean	SD	Min	Max	Med	Q5	Q95
PRICE_PER_SQFT	SGD/sq.ft.	2273.539	1683.275	30.000	32516.000	1815.000	578.100	5453.950
FLOOD RISK	Dummy	0.246	0.431	0.000	1.000	0.000	0.000	1.000
GROUND FLOOR	Dummy	0.284	0.451	0.000	1.000	0.000	0.000	1.000
AVG_ENERGY	kWh/m^2/yr	240.700	111.927	69.446	629.076	208.179	129.252	444.561
AREA_SQFT	sq.ft.	1111.657	13525.850	10.760	748054.940	355.210	161.460	1313.210
DISTANCE_MRT	m	395.729	553.246	9.572	7187.980	223.349	71.210	1720.709
TIME_INDEX	quarter	50.596	28.505	1.000	111.000	51.000	6.000	98.000
LAT		1.309	0.020	1.266	1.442	1.303	1.286	1.354
LONG		103.849	0.035	103.704	103.988	103.851	103.776	103.901

Source: Authors own work.

Table 12. Pearson correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	PRICE_PER_SQFT	1.0000								
(2)	FLOOD_RISK	-0.0733	1.0000							
(3)	GROUNDFLOOR	0.1584	0.1308	1.0000						
(4)	AVG_ENERGY	0.0944	0.2347	0.0637	1.0000					
(5)	AREA_SQFT	-0.0057	-0.0223	0.0034	0.0571	1.0000				
(6)	DISTANCE_MRT	0.0763	-0.2280	0.0361	-0.1914	0.1484	1.0000			
(7)	TIME_INDEX	0.4423	-0.1164	-0.0209	-0.0134	0.0262	0.0681	1.0000		
(8)	LAT	0.0195	-0.1757	0.0335	0.2471	0.0661	-0.0102	0.0503	1.0000	
(9)	LONG	-0.0291	0.1145	0.1072	-0.1287	-0.0105	0.0090	0.2065	-0.3290	1.0000

Source: Authors own work.

4.5 Results and discussion

We estimate the impact of a retail property being located within the flood prone area. Hence, the location might show vulnerability towards flood risk and, therefore, an abnormal purchase price. In addition, we control for several other variables as price determinants. The estimation results of the traditional OLS model are shown in Table 13. Model 1 includes all control variables, while the models 2 to 4 exclude several variables in order to check for robustness and explanatory power.

Table 13. OLS estimation results for log(PRICE_PER_SQFT)

	(1)	**(2)**	**(3)**	**(4)**
FLOODRISK	-0.105***	-0.057***	-0.053***	-0.114***
	(0.020)	(0.020)	(0.020)	(0.020)
GROUNDFLOOR	0.311***		0.304***	0.312***
	(0.017)		(0.017)	(0.017)
log(AVG_ENERGY)	0.309***	0.298***		0.274***
	(0.019)	(0.019)		(0.019)
log(AREA_SQFT)	-0.219***	-0.220***	-0.207***	
	(0.013)	(0.013)	(0.013)	
log(DISTANCE_MRT)	0.018*	0.019**	-0.020**	0.022**
	(0.009)	(0.009)	(0.009)	(0.009)
TIME_INDEX	0.012***	0.012***	0.012***	0.012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LAT	-1.250***	-0.542	0.641	-1.197***
	(0.412)	(0.412)	(0.412)	(0.412)
LONG	-1.276***	-0.804***	-0.788***	-0.845***
	(0.271)	(0.271)	(0.271)	(0.271)
Constant	140.548***	90.760***	89.177***	94.582***
	(28.412)	(28.412)	(28.412)	(28.412)
Observations	6,322	6,322	6,322	6,322
R^2	0.339	0.301	0.312	0.283
Adjusted R^2	0.338	0.300	0.311	0.282
Residual Std. Error	0.571 (df = 6313)	0.587 (df = 6314)	0.583 (df = 6314)	0.595 (df = 6314)
F Statistic	404.843*** (df = 8; 6313)	387.531*** (df = 7; 6314)	408.446*** (df = 7; 6314)	355.926*** (df = 7; 6314)
Notes:	**p<0.1; ***p<0.05; ****p<0.01; White's heteroscedastic robust t-statistic standard errors are reported in parentheses*			

Source: Authors own work.

In the purely linear model, we find that there is a highly significant negative impact of flood risk on retail transaction prices, amounting to an average discount of 10.5% c.p. related to the increased flood risk in the flood-prone area (Model 1). However, the number of properties suggest that retail properties in these locations are, in fact, the exception, that transactions are not very fungible, and that their pricing is not quite customary in the market.

As for the control variables, we identify the story level of the retail unit within the building to be the foremost significant determinant of retail purchase prices in the underlying Singapore sample. On average c.p., ground floor retail units realize 31.1% higher transactions prices than those in basement or higher stories. This seems to contribute to the model significantly as the value of the retail property is largely driven by its rents. Furthermore, it underpins the well-known problem in the market that the upper floors of strata-malls often appear ghostly empty. Rents reflect the potential sales and profit volumes which, again, are influenced by the accessibility, visibility, and, possibly, passerby frequency driving the consumption of goods and services offered. The same logic applies to the size of the individual retail unit, thus being a relevant driver on the investors' side as well. This is confirmed by the model which estimates a discount in the price per sq.ft. for every additional sq.ft. of retail space in a transaction. Furthermore, energy consumption proves to be a statistically significant driver of the analyzed retail purchase prices. However, contrary to expectations, an increased energy intensity has a positive effect on the price. On average, doubling the energy intensity (per square meter and year) adds to the purchase price, on average, by roughly 30.9% c.p. One reason for this could be that energy intensity controls for building age and user comfort, e.g. in terms of air conditioning. The newer the building, the better equipped they are and, in turn, they consume more electricity, with investors willing to pay more for this equipment. Despite being highly relevant for the retail sector in general, the variable DISTANCE_MRT is not significant in this model set up. Changing the model specifications Models 2 to 4 prove the robustness of the results as the target variable and the controls remain significant with only small deviations. It should be noted, however, that the c.p. effect of flood risk is despite robust significance relativized when the variable ground floor and average energy are omitted, from -10.5% (Model 1) to -5.7% and 5.3% (Model 2 and 3, respectively). This could be due to the relatively strong correlation of the variables. Model 1 exhibits an explanatory power of 33.8%, which is the highest among the different model specifications, but still relatively low. This indicates that there might be non-linear relationships which the model does not capture. The enhancement to a GAM model could, therefore, strengthen the explanatory power.

Table 7 displays the estimation results of the GAM model. The linear terms of Model 1 can be interpreted as follows: If the property is located in the defined flood risk zone, the average price discount amounts to 13.5% c.p. and is slightly higher than in the OLS model (10.5% c.p.). The same applies to the location of an object on the ground floor, which has an average price premium of 35.5% c.p. However, energy intensity is in contrast to the OLS model negatively significant, i.e. a doubling of the energy intensity leads to a brown discount of 13.4% on average c.p. We find that this correlation is more in line with previous studies, as mentioned in the Literature Review, and thus recommend the GAM model as the more effective estimate due to the higher volume of variation reflected by the non-linearity of the control variables. The variables AREA_SQFT, DISTANCE_MRT, and the fixed effects modeled as non-linear all prove to be significant.

The models 2 to 4 can confirm the robustness of the results as the variables stay significant. However, Model 2 appears to be an exception as the exclusion of the ground floor variable leads to insignificance of the flood risk term. In general, the explanatory power increased significantly to 69.1% due to the non-linear modeling, which underlines the application and benefits of the GAM model.

For the smooth terms Table 14 displays the estimated degrees of freedom, which range from circa 8.5 to 8.7. Only the interaction term of latitude and longitude exhibits higher estimated degrees of freedom with 29.0 and, as such, strong linearity. The detailed interpretation of the smooth terms is carried out on behalf of the following plots.

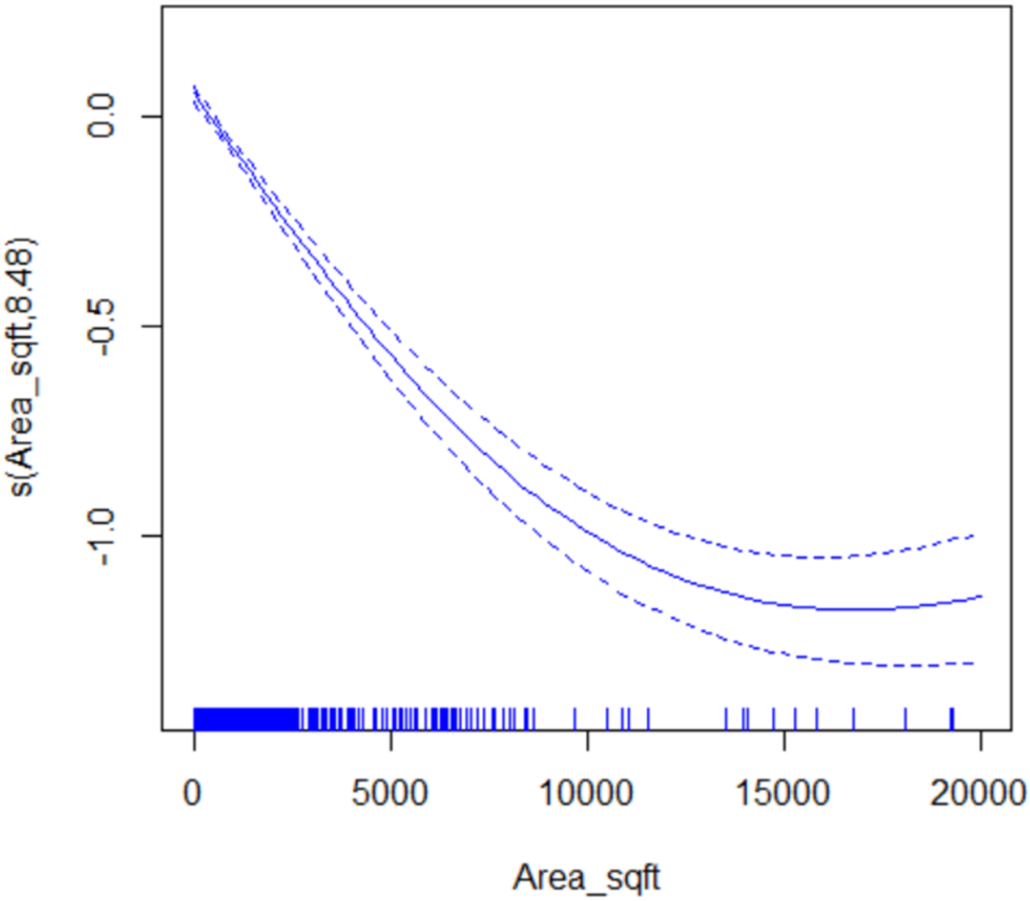
Table 14. GAM estimation results for log(PRICE_PER_SQFT)

	(1)	(2)	(3)	(4)
Linear terms:				
FLOODRISK	-0.135***	0.020	-0.162***	-0.109***
	(0.040)	(0.041)	(0.038)	(0.042)
GROUNDFLOOR	0.355***		0.353***	0.359***
	(0.012)		(0.012)	(0.012)
log(AVG_ENERGY)	-0.134***	-0.105***		-0.147***
	(0.026)	(0.025)		(0.027)
Smooth terms:				
s(AREA_SQFT)	8.483***	8.824***	8.900***	
	(57.72)	(53.50)	(58.34)	
s(DISTANCE_MRT)	8.738***	7.850***	7.907***	8.963***
	(64.78)	(36.97)	(66.20)	(59.68)
s(TIME_INDEX)	8.720***	8.674***	8.687***	8.689***
	(604.10)	(520.40)	(598.98)	(577.14)
s(LAT,LONG)	29.000***	29.000***	28.998***	28.986***
	(162.82)	(138.12)	(188.25)	(158.72)
Constant	8.145***	8.055***	7.431***	8.207***
	(0.138)	(0.132)	(0.011)	(0.144)
Observations	6,322	6,322	6,322	6,322
Adjusted R^2	0.691	0.648	0.690	0.667
Log Likelihood	-3,047.453	-3,464.679	-3,059.808	-3,287.880
UBRE	0.154	0.175	0.154	0.166
Notes:	**p<0.1; **p<0.05; ***p<0.01; the estimated degrees of freedom for the smooth terms are presented; t-values of the linear terms and the F-values of the smooth terms are presented in parentheses*			

Source: Authors own work.

The model identifies retail property area as a determinant of transaction prices. We identify a decreasing tendency in rents per sq.ft. with increasing sizes of the retail units (see Figure 19). The degression of rental prices is estimated to be the strongest up to unit sizes of approximately 5,000 sq.ft. and changes to a slower, exponential decrease of rent prices per square foot.

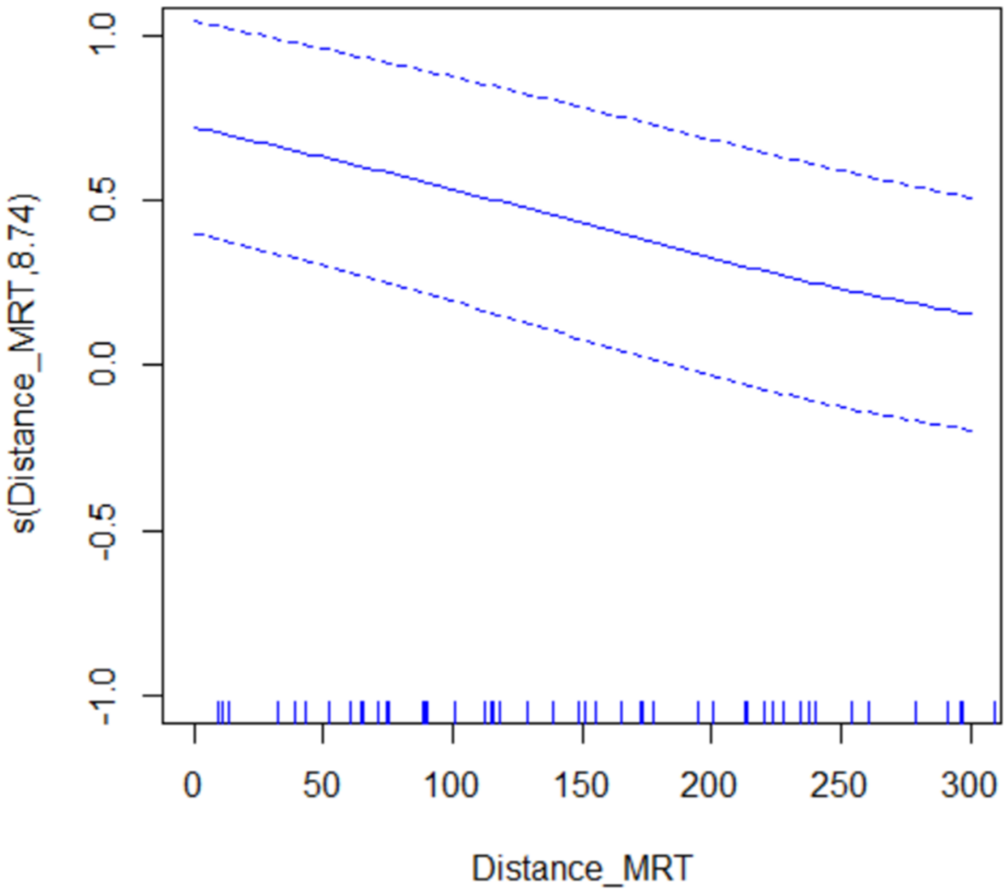
Figure 19. Visualization of retail property area and its estimated impact on transaction prices



Source: Own illustration.

Proximity to the nearest MRT station turns out to be statistically significant, too, in contrast to the linear model. We estimate significant decreases of realized retail property transaction prices exhibiting a highly linear pattern, which seems to flatten out after approximately 150 meters of distance to the MRT (however, with a continuously declining trend, see Figure 20). In this context, there are significant discounts in retail transaction prices if the respective property is located further away from an MRT station. This suggests that a short distance is accounted for as an amenity i.e., in the form of high passerby frequency and related potential for turnover of tenants and their ability to pay rent.

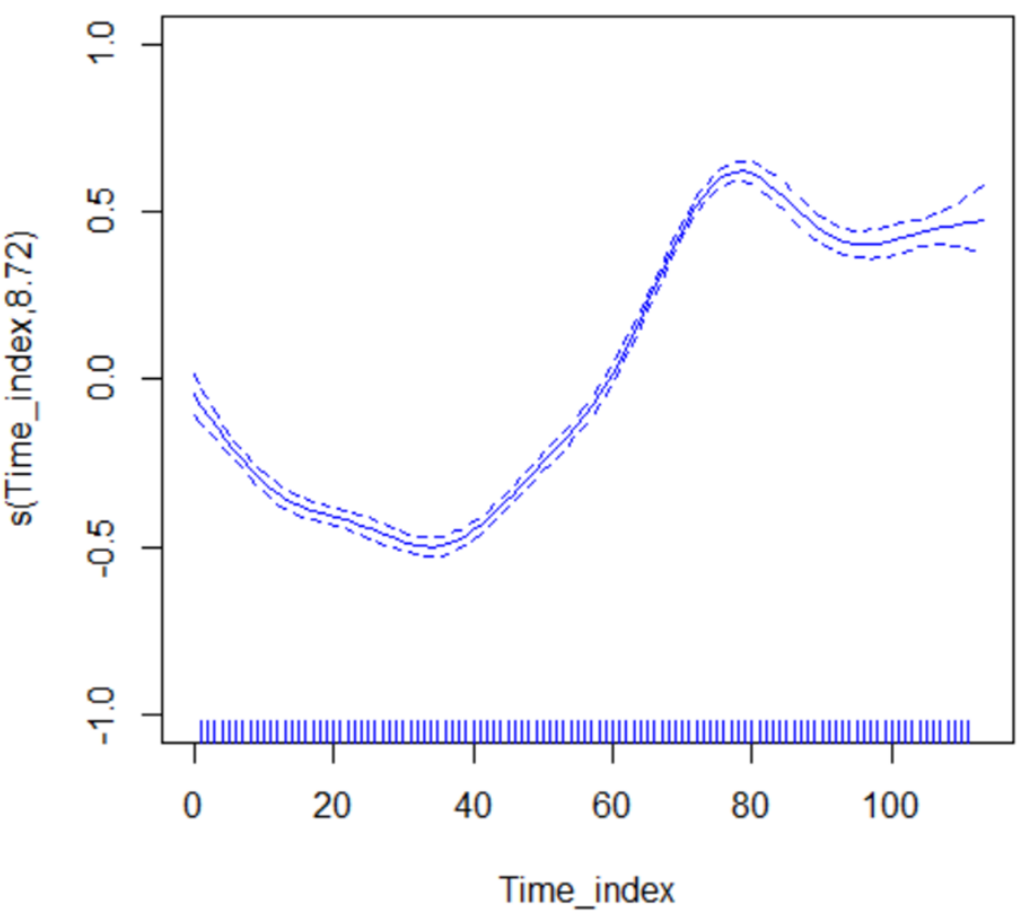
Figure 20. Visualization of distance to the next MRT and its estimated impact on transaction prices



Source: Own illustration.

General market dynamics as measured by TIME_INDEX are highly statistically significant as well and are estimated according to the following pattern on a quarterly basis, as shown in Figure 21. The market movement patterns identified reflect several dynamics. These include substantial reductions in retail property prices in the 1990s and early 2000s, with the inflection point being reached just after the occurrence of the Dotcom crisis, followed by substantial increases in retail property prices going forward. Estimates do not confirm an immediate response to the global financial crisis in 2008/09. However, the peak of retail property prices was reached in the aftermath with a significant time lag of approximately four years after the bankruptcy of Lehman Brothers as the initial event of the incremental crisis. During that time, globalization and increased wealth in Singapore as well as simplified capital raising contributed to a “boom phase” in retail property. After that, market dynamics in the retail sector seem to have outlined lateral movements since 2015, which could be a reflection of the generally decreasing trend of the non-food retail sector as a substantial tenant group. Besides, e-commerce should be expected to have influenced pricing in that period. In addition, many strata malls in particular face decreasing attractiveness towards consumers in comparison to "single-owned" or REIT malls, as agreements in terms of modernization investments or in terms of tenant mix and quality are harder to achieve with a magnitude of part-owners.

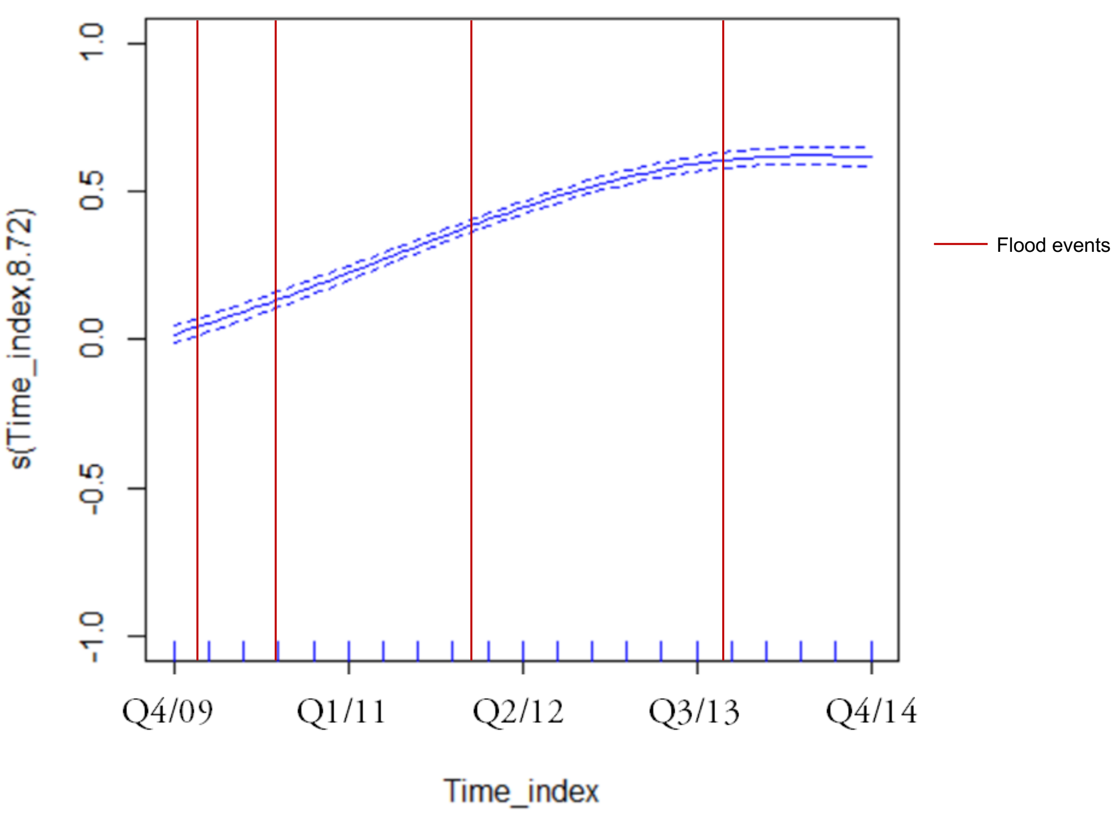
Figure 21. Visualization of retail property market dynamics between 1995 and 2022



Source: Own illustration.

In terms of market dynamics and timing, this study does not seem to confirm the theories on property price responses on flood events (bounce-back effect, myopia, or similar, see Literature Review). As shown in Figure 22, the four latest significant flood events (shown as red lines), did not essentially impact overall market dynamics in terms of strong bounce backs or the like. However, we observe a certain flattening of property price increases up to stagnation after the last event, which might be due to the ongoing yield compression environment in the past years. Generally, we expect that these market dynamic estimates account for increased flood risk adaption measures which have been in place since the last catastrophic events of global extent in 1954, thereby reducing the price responses to impulses from specific flood events. In other words, the occurrence of specific flood events does not seem to have been severely harmful to market dynamics in the retail property sector. However, as outlined before, the general flood risk (independently of specific events) seems to be a significant determinant of property prices, nevertheless.

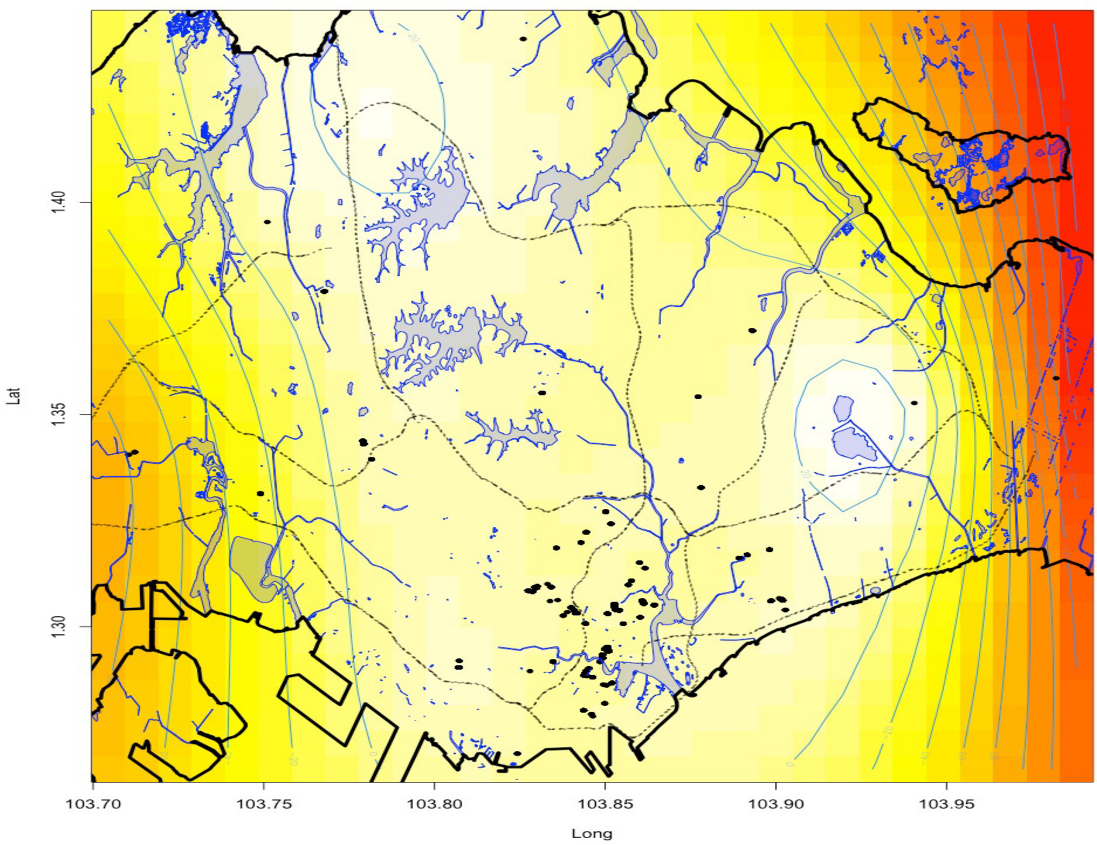
Figure 22. Visualization of retail property market dynamics between 2009 and 2014



Source: Own illustration.

The geospatial distribution of the market within the borders of Singapore is illustrated in Figure 23. Based on data on the latitude and longitude of the retail units, we understand that there are several neighborhood effects as explaining factors, such as different levels of quality, profitability, and pricing power among the surroundings of the retail units. More specifically, there seem to be two major "hot spot" areas in terms of geospatial effects on pricing (indicated by white background) as well as a price premium in the Central Region as well as isolated premiums in North Eastern as well North Western areas.

Figure 23. Geospatial effects of property location in retail markets



Source: Own illustration with geo data of OpenStreetmap.

4.6 Conclusion

The risks related to extreme weather events are constantly rising in terms of frequency and intensity as well as probability of damage. In addition, climate change is changing patterns of flooding by adding another source of hydrological risk to considerations of investors and property owners. In this context, this paper raised the question, whether retail property markets in Singapore account for these risks in their inherent pricing structure and, if so, to what extent they reflect possible future property and financial losses in their transaction prices.

This study finds that we cannot confirm that Singapore's retail property market is ignoring flood risk and potential financial damages arising from it. Instead, it actually accounts for it as a statistically significant determinant within its transaction pricing by reducing retail property prices in the particular risk area by, on average, 13.5% c.p. We assume that this discount is priced in to reflect potential losses from additional repair and maintenance costs, possible loss of rent or turnover, as well as additional inconvenience from shutdowns during extreme weather events. Moreover, a certain probability of total loss might be reflected in the price discount due to the external flood risk.

We also find that this effect is rather invariable over time. Specifically, we cannot confirm the bounce-back effect or amnesia and myopia which are suggested by the literature. Instead, the retail property market in Singapore seems to be indifferent towards particular flood events. Market dynamics in general seem to be unaffected even after hydrological extreme weather events. This confirms our conclusion that, most likely, transaction prices already considered the present flood risk financially at the time of acquisition.

We identify several explanatory factors that determine transaction pricing, including, very clearly, the size of the retail property as the driver of turnover and rent of the property, as well as visibility and access on ground floor levels. Furthermore, the location itself as well as energy consumption apparently drive transaction pricing significantly. Finally, the distance to the next major public transport seems to contribute to the understanding of transaction prices.

The findings in this paper are subject to several limitations. Firstly, we are focusing on Strata-titled retail units. While they are sold and rented out for long-term investments by institutional and private investors, the share of owner occupiers is relatively high. Pricing, therefore, may be following operational considerations such as achievable turnover rather than achievable rents, which should be expected to be an important driver of pricing for REIT or single-owner malls. Secondly, due to the long-time span (27 years) of observations in the sample, changes in macro-regional developments within the city may have happened but have remained unconsidered in terms of their impact on property pricing. Specifically, changes in the MRT network may have occurred that may or may not have caused price leaps or drops in particular neighborhoods over time.

This lends itself to opportunity for further research to overcome stationary effects, for instance, by applying more machine-learning oriented methodology such as neural networks. We draw upon the argumentation in Hirsch and Hahn (2018) and argue that the results of a particular flood risk study in property markets have mostly regional validity. Hence, there is certainly a lot of potential in the regional expansion of flood risk studies in countries around Singapore, which show high exposure to hydrological risk.

4.7 References

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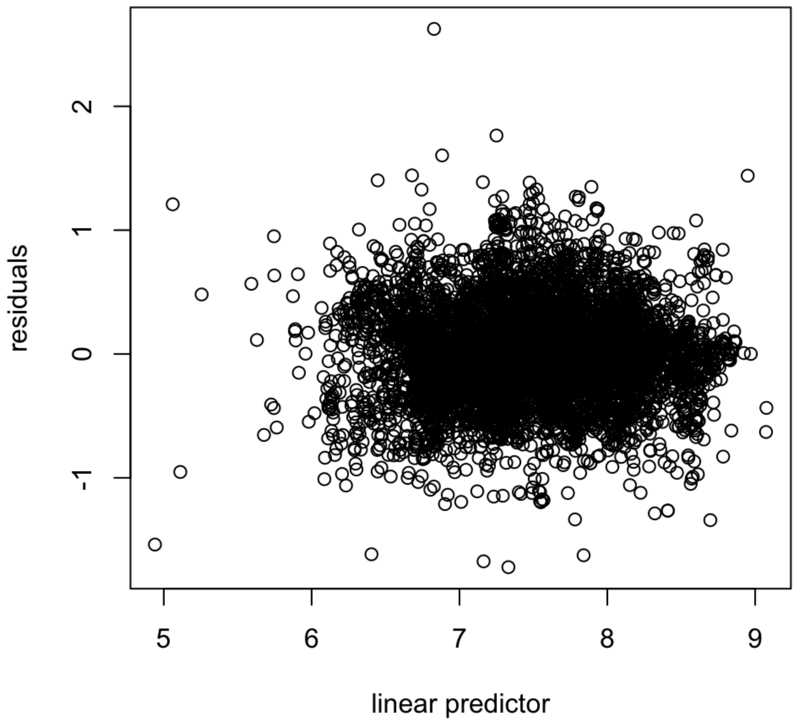
4.8 Appendix

Residual check for heteroscedasticity of GAM Model 1

Figure 24. Residual check for heteroscedasticity of GAM Model 1



Source: Own illustration.

5. Conclusion

5.1 Executive summary

In the following, the three papers are summarized and an overview of the addressed problems and objective, data and methodology as well as the results and their contribution to science and practice is given.

The paper **Deterministic or Stochastic? The Volatility of US Commercial Real Estate Returns** deals with the risk of asset volatility of capital value returns. The existing body of literature, which is mainly based on GARCH models, assumes a deterministic volatility process across time, i.e. a relationship between the current volatility and past returns as well as past volatility. However, theoretical drivers such as the inefficiency of property markets and irrational behavior of market agents, can lead to significant shifts or structural breaks, which rather advocates a stochastic volatility process. Therefore, the objective is to apply a stochastic volatility model to commercial real estate and compare the goodness of fit to its deterministic peer. The study uses monthly capital value log returns from the RCA CPPI from January 2001 to December 2021. In total nine indices for the US are modelled, which contain besides the National All Property Index the commercial, retail, industrial, office, office (CBD), and office (SBD) index. The methodology includes the estimation of the SV models and the commonly known GARCH models as benchmark. Furthermore, the estimation procedure is a Bayesian approach using MCMC sampling to generate posterior predictive distributions, which is used for both models to provide comparability. The results reveal evidence for the existence of stochastic features in the data generating process as the biases between the observed samples and the posterior predictive distributions in the SV models are lower compared to those in the GARCH models. Still, the degree of improvement varies between the property types. For retail properties the different goodness of fit measures suggest a Stochastic Volatility model with first autoregressive order (SV-AR1) rather than the different GARCH variations. Moreover, modelling higher orders of autoregressive terms does not necessarily appear to be important compared to the other observed indices, where the SV-AR2 models exhibit the highest goodness of fit. The results contribute to science by providing a novel, superior solution to model commercial capital value volatility.

Further research in the field of SV models for other numbers of interest such as income or total returns as well as multivariate approaches are suggested. Moreover, SV models deliver immense value of accuracy improvement when being incorporated into risk management practice to forecast volatilities.

In this dissertation, improvements on climate risk management are introduced by the paper **The Underestimated Global Warming Potential of Refrigerant Losses in Retail Real Estate: The Impact of CO2 vs. CO2e,** focussing on transitory climate risks. The Kigali Amendment to the Montreal protocol and the EU F-gas regulation aim to drastically phase-out F-gases used as refrigerants in buildings as they can have an up to 5,000 times higher impact to global warming than CO2. As of 2020, over 60% of central refrigeration systems in operation in food retail properties in Germany still use such environmentally harmful refrigerants. However, there is no evidence regarding the actual share of F-gas emissions on total building emissions for retail assets. Therefore, the objective of the paper is to measure the emission level of F-gases in food retail properties in Germany. While real estate companies started to benchmark CO2 emissions from electricity and gas consumption, they lack concrete consumption data and reference values of refrigerants. Without this awareness market participants are not able to account for transitory risks arising from increasing refrigerant costs or market expectations. For the analysis energy consumption and refrigerant leakage data from 2019 of 29 retail properties located in Germany was used. To measure the resulting CO2 emissions of the energy consumption as well as the CO2e emissions of the refrigerant losses on asset level the CRREM tool is implemented. Furthermore, a paired samples t-test is carried out to confirm or reject an effect on the emission levels of the analysed assets. The results show that F-gases account for 40% of total emissions and nearly 45% of cumulative emissions until 2050, on average. This implies high relevance for retail properties as the commercial average share is 1.8%. Additionally, the results are robust examining the t-test. The findings contribute to science to underline the fact that the impact of food retail properties and associated refrigerant losses is still highly underestimated in the real estate sector. We strongly suggest further investigations on the actual quantitative risks from F-gases for real estate investors.

The final paper **Do retail property markets in Singapore ignore flood risk as a natural hazard?** rounds off the core part of the dissertation with an examination of physical climate risk. The city state Singapore and its properties are subject to this risk, which is mainly driven by extreme weather events such as flood events from heavy rain and related externalities such as landslides. Given the potential damage rational investors would price in the discounted losses from expected damages into their investment activities. Thus, the paper aims to provide evidence on whether the retail real estate market in Singapore does consider flood risk in its inherent pricing mechanisms. The study is based on a data set of 6,322 address-level observations of retail transaction prices between 1995 and 2022. It covers strata-titled retail units in a total of 80 different shopping malls across Singapore. Additional to several included hedonic attributes such as the size of the unit or the storey, the distance to the closest MRT station and the flood risk exposure as well as the energy performance of the shopping mall are added. The estimation is proceeded by means of a GAM with the transaction prices as dependent and the flood risk as explaining target variable. Results confirm that retail investors do not ignore flood risk and potential losses, but rather account for it in transaction pricing. On average, retail units within a flood prone area exhibit a discount of 13.5% c.p. and furthermore, market dynamics seem to be unaffected, even after occurring extreme events. Not related to the subject of physical climate risk but still enriching is the result, that high energy consumption leads to a discount in the transaction price. In summary, the study adds to the science and practice as empirical analysis on the effect of physical risks in Asia as well as retail properties in general is rather limited, although highly affected in the future.

5.2 Final remarks

The investment market for retail real estate has become increasingly complex in the past and will continue to intensify in the future. Investors are familiar with the risks arising from increasing interest rates, inflation or energy prices from the past and have built up corresponding risk controlling systems. These need to be strengthened in order to be even better positioned to deal with future shocks and associated strong asset volatility.

On the one hand, this work aims at improving risk management techniques. For capital value returns in the US, the dissertation provides evidence that the volatilities of these are of stochastic and not deterministic nature and therefore SV models are a superior approach compared to the GARCH models currently used in research and practice. It is now necessary to achieve awareness for this insight and broad application in risk management. Further research is needed to prove a stochastic behavior of the volatilities of also cash flow returns and total returns, and that this characteristic is not limited geographically to the US market, but also holds for popular retail property markets such as Europe and Asia. Additionally, it is worth considering that currently, the model only has a univariate form. Hence, there is potential to increase the accuracy of the posterior predictive distribution of volatility through a multivariate extension. One way to achieve this would be by incorporating macroeconomic factors such as inflation or interest rate developments into the SV model as a factor model. This suggestion has been made by e.g. Hosszejni and Kastner (2021) or Yilmaz and Selcuk-Kestel (2018) and has the potential to significantly improve the model’s goodness of fit.

The World Economic Forum's (2023) Global Risks Report highlights the fact that investors should not just focus on improving the management of well-known risk factors. Very few market players are prepared for climate change and the associated transitory and physical risks, and therefore the dissertation aimed to identify and quantify these "new" risks for retail real estate.

On the side of transitory risks, it is evident that F-gas emissions in terms of refrigerant losses are still an underestimated factor and thus also a risk. With an average share of 40% of total emissions, F-gases have a significant impact on the CO2e performance of food retail properties in Germany, which few property owners are aware of. However, the switch to alternative refrigerants is urgently needed as the EU continues to reduce the volumes of F-gas based refrigerants on the market, driving up purchase prices. The findings should encourage investors to create a profound data basis for F-gas emissions in order to become aware of their own emission volumes. In the next step, based on that knowledge the monetary effects must be determined. Further focus of research could be, for example, the prediction of refrigerant prices and volatilities analogous to the body of literature on carbon price predictions (see Oertel et al., 2022; Kim et al., 2017).

Regarding physical climate risks, it is evident that investors already seem to be aware of them. In Singapore, the location of retail properties in flood prone areas is reflected in the transactions with a price discount of 13.5% on average c.p. This is an interesting finding since the city has already implemented several measures to adapt to physical climate risks, including flood risk, but these do not yet seem to be sufficient for investors to avoid any potential costs. In addition, these results are particularly helpful to cross border investors who do not have such deep location knowledge. More in-depth studies for other cities in Asia, such as Bangkok or Hong Kong, would be informative due to their exposure to physical risks.[12] In addition, other extreme weather events such as typhoons would be of urgent interest.

To conclude, there remains a viable opportunity to persist in investments in retail real estate, thereby capitalizing on the potential for enhanced returns. Yet, the prerequisite for this is to further strengthen risk management and to proactively familiarize oneself with the worst-case scenarios of the IPCC today in order to be able to fully price the risks of climate change into investments. Turning a blind eye and being reactive will cost investors dearly in the future.

[12] Hong Kong experienced on 8 September 2023 the heaviest rainfall since records began in 1884 flooding several shopping malls in the city.

5.3 References

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