Band 99

Cay Oertel

Risk Management in International Real Estate and Capital Markets

International Real Estate Business School
Universität Regensburg

Schriften zu Immobilienökonomie und Immobilienrecht

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Die Deutsche Bibliothek – CIP Einheitsaufnahme
Cay Oertel
Risk Management in International Real Estate and Capital Markets
Regensburg: Universitätsbibliothek Regensburg 2021
(Schriften zu Immobilienökonomie und Immobilienrecht; Bd. 99)
Zugl.: Regensburg, Univ. Regensburg, Diss., 2020
978-3-88246-441-2

978-3-88246-441-2

Verlag: Universitätsbibliothek Regensburg, Regensburg 2021
Zugleich: Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaften, eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg
Tag der mündlichen Prüfung: 22. Juli 2020
Berichterstatter: Prof. Dr. Sven Bienert
Prof. Dr. Steffen Sebastian

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Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

eingereicht an der Fakultät für Wirtschaftswissenschaften der Universität Regensburg

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Tag der Disputation:

22. Juli 2020

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1 Introduction

1.1 Risk in real estate, the impact of securitization and derived research

The presence of *risk* is an essential part of finance since risk-taking is the natural economic necessity to generate excess returns (dating back to Knight, 1921). Although a single and unanimously accepted definition of the term is missing across different sciences, the meaning of risk in finance entails two decisive elements: The potential of a negative divergence from expected values and a corresponding monetary loss due to the negative divergence (McNeil et al., 2015).

Based on these two components, the term risk in academia is strongly connected to *uncertainty* and *randomness*. Investors face situations in which the future financial performance of assets, like real estate, is uncertain. Thus, any decision entails *ex ante* uncertainty about its outcome in the future. In terms of statistical language and real estate, the interpretation is that these risks or concrete risk *factors*, such as rental growth, maintenance expenses, construction costs, financing costs, etc., are modelled as *random variables* in *ex ante* financial models (French & Gabrielli, 2004).

Financial risk management has focused on the application of *probability theory* to model these random variables in a decision under uncertainty. According models were introduced by Kolmogorov (1933) to oppose purely deterministic models. This pioneering work still provides the common terminology for risk-related scientific discussion. The application of probability in the real estate literature and in the context of risk represents the class of so-called *stochastic models*. In contrast to deterministic models (explicitly introduced and described for real estate assets by Mollart, 1988), their stochastic peers allow the *explicit* modelling of risk using the corresponding distribution functions of the risk factors in the future to account for their randomness (as pointed out by e.g. Hoesli et al., 2006; Pfnür & Armonat, 2013).

The financial risk management of investment positions is implemented in practice by institutional investors using a comprehensive and recursive risk management *system*, which is supposed to ensure the identification, quantification, steering, and surveillance of risks. This procedure applies to investors of classic capital market products, such as stocks or bonds and alternatives, like real estate mostly alike, because legal requirements generally do not differ between the assets of the investment company. In this context, a clear development of legal tightening can be observed in the aftermath of the global financial crisis in 2008.[1] Additionally, risk management has moved into the center of attention from an economic point of view because of concerns about potential over-valuations of property assets have risen due to the extensive global monetary expansion (Hayunga

[1] In Germany, for example, the introduction of the "*Kapitalanlagegesetzbuch*" in 2013, and subsequently the "*Mindestanforderungen an das Risikomanagement von Kapitalverwaltungsgesellschaften*" in 2017. Both regulatory adjustments are based on European law, namely the Alternative Investment Fund Manager Directive (AIFMD), illustrating an international scale of regulation.

& Lung, 2011; Abildgren et al., 2018; Fabozzi & Xiao, 2019) and the economic turmoil due to the COVID-19 pandemic.

However, the concrete methodological implementation of a stochastic approach is subject to the *asset class specifics* of the managed positions. These asset class specifics are highly relevant for the present thesis because the articles address the abovementioned types of products: Firstly, alternative investments like direct real estate and secondly, classic investment products like stocks including securitized real estate and bonds. The decisive mechanism that separates the articles and the methodology is the *securitization* function of indirect investment vehicles in capital markets. On the one hand, direct real estate as an asset class can be characterized as heterogeneous, illiquid, having high transaction costs and durations, and entailing low fungibility and transparency (or information respectively), among others.

Indirect or securitized real estate, on the other hand, transforms these specifics of the underlying properties. Accordingly, the risk management methodology changes as well, because capital markets provide homogeneity, liquidity, fungibility, information, relatively low transaction costs and durations. Due to the named specifics of public equity positions, the corresponding risk management was methodologically heavily driven by the capital asset pricing model introduced by Sharpe (1964), as well as the volatility modelling of Bollerslev (1986). Lastly, debt positions focus methodologically on aspects arising from the individual credit agreement and the borrower (a comprehensive and basic risk model overview for debt positions can be found in Crouhy et al., 2000), urging to model metrics like probability of default (PD), loss given default (LGD) or exposure at default (EAD), etc. (for an overview on the diversity of risk management approaches across the specified asset classes, see Booth et al., 2002).

The modelling within the real estate industry focused historically on qualitative approaches to manage the risk of their positions. However, due to the legal requirements as well as higher data availability and probability functions of risk factors (Amédée-Manesme & Barthélémy, 2018), more quantitative approaches including stochastic modelling in the sense of Kolmogorov (1933) have been established. Accordingly, for direct real estate, the most feasible stochastic approach to quantify the *residual risk* of the assets is the Monte Carlo Simulation (MCS; Hoesli et al., 2006; Baroni et al., 2007). The reason for this approach is the missing applicability of the models of other asset classes, as described above. For the simulation of the cash flows of the properties, however, the macroeconomic environment and the relevant risk factors of the assets need to be identified correctly because real estate assets are highly dependent on the macroeconomic circumstances (as comprehensively described by Clayton, 1996). Central for this modelling is the question, what risk factors can affect the cash flows of the property? Therefore, it is crucial to identify the *functional chain* in risk factors models (e.g., as described by Ho et al., 2015) before quantifying the impact on the individual asset level. The thesis derived the following selected aspects of risk management in international real estate and capital markets based on these considerations of risk identification, quantification, steering, and surveillance in direct as well as securitized real estate markets.

The first article of the thesis presents a typical fundamental risk factor model described above. It aims at assessing the potential impact of domestic and global economic political uncertainty on commercial real estate markets. Recently, politics-related uncertainties like Brexit have gained large interest (French, 2019). However, the existing body of literature has mainly focused on residential markets in this context (e.g., Monfared & Pavlov, 2019). Thus, the paper "*The relationship between domestic and global economic political uncertainty and European direct commercial real estate returns*" estimates linear models to isolate the effect of the target covariates on total returns of office properties in Europe. Additionally, the independent covariates are divided into domestic and global economic political uncertainty to find thinkable cross-border effects of uncertainty after controlling for the domestic peer to detect a potential "safe haven effect," namely a positive influence of foreign uncertainty on domestic properties.

The second article on direct property markets "*Do Cross-Border Investors Benchmark Commercial Real Estate Markets? Evidence from Relative Yields and Risk Premia for a European Investment Horizon*" addresses the determinants of cross-border investment flows in real estate markets. So far, literature has widely focused on economic or institutional *pull* factors, which attract capital (e.g., Lieser & Groh, 2014). The article extends the existing literature by constructing a synthetic index for European investment locations to test for the relative attractiveness of a market as a determinant of inflowing capital. Methodologically, linear as well as non-linear regression models are used for European panel data. Nonetheless, one may ask about the connection between foreign capital flows and risk management. Market liquidity of direct real estate markets can be an important risk factor, which may cause deviations from expected values of, e.g., transaction durations, time on the market, etc. Thus, the article contributes to the understanding of the underlying functional chain of market liquidity, which is a commonly known risk factor.

Next, the thesis turns towards the risk management of securitized real estate positions in capital markets. As outlined above, the transformation functions of indirect vehicles allow investors to steer the risk of their indirect positions differently from their direct peers. Here, the paper *"Volatility Targeting for US Equity REITs – A Strategy for Minimizing Extreme Downside Risk?"* presents the so-called *Volatility Targeting* rebalancing algorithm for REIT securities as an active management tool for risk steering. Since daily returns of REITs are showing even stronger volatility clustering and leverage effect than classic equities (Cotter & Stevenson, 2007; Jirasakuldech et al., 2009), the asset class appears to be very promising for research on volatility-based risk strategies. To the author's knowledge, no article has carried out an empirical study on the specified technique of REIT securities to analyze the characteristics of REIT volatility explicitly from an applied risk management point of view. To provide insight, at first a back testing approach simulates returns from the volatility targeting algorithm. The strategy bases on various volatility estimators, such as historical volatility, the CBOE Volatility Index based on broader stock market option prices, and on one-day-ahead forecasts of a generalized autoregressive conditional heteroscedasticity (GARCH) model. The realized returns of the strategies are then analyzed in a portfolio optimization framework to identify the strategies' economic efficiency compared to a classic buy and hold investment scenario.

The last paper extends the investment horizon to classic stocks and bond positions. The paper "*AR-GARCH-EVT-Copula for Securitized Real Estate: An approach to improving risk forecasts*" is the first study to apply the so-called AR-GARCH-EVT-Copula model to bivariate portfolios, which contain securitized real estate in addition to the abovementioned capital market products. Different from the previous article, this paper does not aim at economic efficiency and its frontiers but forecasting price risk metrics. The primary motivation for the paper is the stylized facts about financial market data. The data have repeatedly shown leptokurtosis, skew and fat tails (largely discussed by McNeil & Frey, 2000), which provokes the application of a GARCH-standardization to model the dependency of securitized real estate and other asset classes. In addition, dynamic and asymmetric dependency appears to be necessary since real estate is an asset class, which co-moves to stocks and bonds in timely variant, skewed, and over-proportional fashion. The approach aims at solving for the named issues and compares the method to classic historical simulation or variance-covariance method to obtain appropriate price risk metric forecasts. Based on the entire aforementioned derived research, the following questions are central for the empirical studies of the thesis:

1. ***The relationship between domestic and global Economic Political Uncertainty and European Direct Commercial Real Estate Returns***

I. Does domestic economic political uncertainty affect total returns of direct office property investments?
II. Is foreign economic political uncertainty a driver of domestic direct commercial property returns?

2. ***Do Cross-Border Investors Benchmark Commercial Real Estate Markets?* Evidence from Relative Yields and Risk Premia for an European Investment Horizon**

I. Is there a relationship between the relative yield or risk premia attractiveness of an investment location and inflowing cross-border transaction volumes?

II. Is there empirical evidence for a non-linear relationship between the relative attractiveness proxy and inflowing cross-border transaction volumes?

III.

3. Volatility Targeting for US Equity REITs – A Strategy for Minimizing Extreme Downside Risk?

I. Is the application of Volatility Targeting for US Equity REITs economically efficient compared to a benchmark buy and hold strategy in a mean-tail-risk-optimization framework?

II. What volatility measurement provides the highest economic efficiency in the mean-tail-risk-optimization framework?

4. AR-GARCH-EVT-Copula for Securitized Real Estate: An approach to improving risk forecasts?

I. Does the AR-GARCH-EVT-Copula approach provide more accurate price risk metric forecasts compared to the variance-covariance or historical simulation method?

The thesis is structured as follows to provide insight. The next chapters reproduce the empirical studies that are related to the abovementioned research questions. Every article is introduced by a page that states the full list of authors in the order of the publication, the status of the article, and a short abstract. The abstract matches the submitted or published article abstract in case the respective medium reports an abstract. In case this does not apply, an unpublished abstract has been added. The last chapter contains the conclusion stating a summary of the articles, the definite answer of the derived hypothesis, the joint conclusions of the thesis, the research limitations, and potential future research in real estate risk management.

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2 The relationship between domestic and global Economic Political Uncertainty and European Direct Commercial Real Estate Returns

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Journal of European Real Estate Research (Revised)

Abstract

The aim of the study is to investigate the impact of domestic as well as global economic political uncertainty on direct real estate returns at the European City-level. The empirical study uses OLS estimation for a European direct real estate panel data set containing 20 cities across 9 European countries, with quarterly observations from Q1/2008 – Q3/2018. After controlling for empirically proven explanatory covariates of total returns, the model is extended by proxies for domestic and global political uncertainty. The study finds c.p., on average a statistically significant lagged negative influence of domestic economic political uncertainty on European direct commercial property total returns. Global economic political uncertainty c.p. positively affects total returns, indicating a "safe haven effect".

2.1 Introduction

Economic political uncertainty (EPU) has recently moved into the center of attention. Brexit, the severe military tensions between the US and Iran, US-Chinese trade conflict, civil right activism in Hong Kong and persistent worrying signs from North Korea, all of which affect the international community are just a few prominent examples of a seemingly endless list of current political uncertainties with a potential economic impact. In this uncertain global environment, European real estate markets have been considered a "safe haven" for investors. Nonetheless, due to increased political uncertainties for example in the UK, the issue has reached European market participants as well (French, 2019). The question inevitably arises for market participants, as to whether and how this current domestic EPU (DEPU) is affecting real estate returns. The literature has repeatedly shown the impact of DEPU on direct residential property returns (e.g. Monfared & Pavlov, 2019). Does this also apply explicitly to commercial real estate returns and EPU in Europe?

Additionally, for various reasons not only domestic but also non-domestic or global economic political uncertainties (GEPU) may also reveal contagious spillover effects on European property returns. Most importantly, due to its central geographic location, Europe can be assumed to be exposed to GEPU. Secondly, European economies are well-developed and thus globally integrated, for example through intense trade-related dependencies. Accordingly, these locations are expected to be more dependent on the global political environment, due to strong international economic connections (e.g. as recently discussed regarding European markets and the US by Oertel et al., 2019).

There is a literature on the impact of non-fundamental drivers such as EPU on real-estate-related parameters. However, these articles generally include market sentiment in terms of the economic environment, in order to quantify the impact on property market agents (e.g. Clayton et al., 2009; Marcato & Nanda, 2016). To the best of the authors' knowledge, there is no empirical study that isolates the impact of uncertainties from the economic *political* environment on direct commercial property returns. Accordingly, the central research question can be formulated as follows: Is there a statistically significant relationship between EPU and direct commercial real estate returns?

The article contributes to the existing body of literature in several ways. It is the first article to show the relationship between European and especially city-level direct commercial property returns and EPU at both the domestic and global levels. By contrast, previous articles have focused on national-level index housing data in the US (e.g. Antonakakis et al., 2015). Secondly, not only country-specific DEPU is assessed, but also GEPU as a potential factor that influences direct real estate returns. Thus, the relationship is expanded by analyzing not only the relationship at the individual level, but also with regard to the entire global environment.

The study is structured as follows. The next section outlines the theoretical related literature and derives the hypotheses for the empirical work. Based on the literature, the research design including the measurement for both types of EPU is described. The underlying data and the control variables for isolating the impact of the target variables are then explained. The ensuing sections contain the methodology and the empirical results. The final section concludes, describes practical implications and designs potential further research possibilities.

2.2 Theoretical background, related literature and hypotheses derivation

The present study considers total returns as the dependent variable of interest. The underlying theory for connecting EPU and returns stems mainly from a behavioral approach, which assumes investors to be affected by assumptions about future cash flows and investment risks (Baker & Wurgler, 2007). In order to derive the hypotheses and the methodological approach for a new empirical study, the literature on the following two issues needs to be considered: Theoretical transmission channels of DEPU and GEPU on total real estate returns, as well as existing empirical studies on other determinants of the specified returns. The latter part of the literature review is required to justify of the control variable set.

According to basic real estate theory, property returns are generated from changes in capital values and income (as formally expressed by the IPD):

$$TR_t = \frac{CV_t - CV_{t-1} - C_{exp,t} + C_{rec,t} + NI_t}{CV_{t-1} + C_{exp,t}} \qquad (1)$$

where the total return, TR_t, is a function of the capital values CV in the current (t) and previous period $(t-1)$, total capital expenditures, $C_{exp,t}$, capital receipts, $C_{rec,t}$, and the net income NI_t. The capital values can be broken down into more granular components, as formulated, for example, in Gunnelin et al. (2004):

$$CV_t = \sum_{t=1}^{T} \frac{R_t}{(1+i)^t} + \frac{R_T}{(1+i)^T(c-g)} \qquad (2)$$

where R_t denotes the net rental income, discounted by the rate i. In the terminal period, R_T is capitalized by an exit capitalization rate (c) less an expected growth rate of cash-flows (g). The exit capitalization rate can further be decomposed by the Gordon model into risk-free interest rf, and a risk premium for placing capital in a property investment, rp:

$$c = rf + rp \tag{3}$$

Given these equations, the theoretical mechanisms for non-fundamental determinants such as EPU to affect the total returns, can be described. Firstly, the CV_t can be affected by the assumptions made by market participants about the abovementioned risky components of the future rental income components across the holding period, $R_t,\ t \epsilon (t, \dots, T)$. As noted by Ball et al. (2009), the rental income generation of commercial properties is time-lagged dependent on economic performance. Economic performance again is partially a function of EPU (Smales, 2017). Secondly, increased uncertainty can also increase discount rates i, leading to a higher "penalization" of future cash-flows, and vice versa.

Lastly, the EPU can transmit through the exit capitalization (c) of the property by means of a higher risk premium (rp) in equation (3). These premia on exit capitalization rates are dependent on the assumptions and perceptions of market participants, as noted by Netzell (2009). Hence, it can be assumed from a theoretical point of view, that a statistically significant effect of EPU on the total returns is driven substantially by the appreciation return side. This assumption can be connected with the study of Chaney & Hoesli (2012), who identify the cap rates of commercial real estate as statistically significantly impacted by sentiment, thus potentially also by EPU. Since cap rates are highly relevant for the appreciation expressed in equations (2) and (3) above, this may provide an explanation. Due to the long-lasting nature of real estate rental agreements, however, this general finding should be evaluated as economically trivial.

For the income side on the other hand, the decisive determinants are net income receivables as a percentage of capital employed. These receivables from property investments are dependent on vacancy rates and expected rental growth (Gunnelin et al., 2004). Such receivables are theoretically potentially negatively affected by EPU through assumptions made by market agents, if potential tenants reduce their space demand or by negative rent growth, reducing NI_t. However, due to the above mentioned potential long-term rental agreements, especially short-term shocks in EPU are theoretically substantially eased for the income side of office property investments.

The empirical literature on non-fundamental determinants of property returns dates back to the work of Case & Shiller (1989), who introduce the impact of sentiment and the respective indices on residential property markets. Ensuing articles on residential and commercial real estate returns have broadly confirmed a statistically significant relationship between economic market sentiment and real estate market parameters and especially direct returns (e.g. Clayton et al., 2009; Tsolacos et al., 2014; Ling et al., 2015; Marcato & Nanda, 2016).

Based on this broader term of market sentiment, the politics-related component of DEPU has been analyzed in only a few articles in the real estate literature. Monfared & Pavlov (2019) recently showed the impact of political uncertainty or risk on housing prices in London, by estimating difference-in-difference models to isolate the impact of the 2016 Brexit referendum. Since this study assessed a single political event, the universality of the results should nonetheless be questioned. Additionally, Antonakakis et al. (2015) modeled the time-varying relationship between DEPU and housing market returns for the US in a GCC-GARCH framework for conditional mean and variance estimation. The authors find evidence of a statistically significant negative impact of DEPU on the conditional mean and a positive impact on the conditional volatility. From a methodological point of view, the parameterization of conditional volatility models in direct real estate markets is problematic, due to the typically low frequency and absolute number of observations.

In addition to DEPU, the literature has also incorporated its foreign or global counterpart to explain domestic real estate market parameters. Badarinza & Ramadorai (2018) isolate a statistically significant positive effect of foreign country EPU on prices in the residential real estate market of London. However, the underlying explanation of increased migration, especially from countries with large migrant groups such as Russia, cannot be applied to commercial properties. For commercial real estate properties on the other hand, and from a theoretical perspective, GEPU does not impact on total returns through the abovementioned transmission channel of migration and the associated space demand. In this context, the decisive factor may be global economic integration and transmission due to spillover effects. In this respect, Colombo (2013) has shown that political uncertainty in the US leads to statistically significant negative shocks to European productivity and thus to economic stability. Accordingly, as for its domestic peer, the GEPU is expected to negatively affect direct property returns.

These considerations about domestic and global EPU as part of market sentiment should then logically be linked to the body of existing empirical studies on determinants of direct real estate returns, so to as review other relevant variables, which are subsequently methodologically valuable as controlling covariates. Generally, the literature on determinants of direct real estate returns splits the relevant parameters into macroeconomic and property-related variables (e.g Ling, 1997; Kohlert, 2010; Akinsomi et al., 2018). On the macroeconomic side, various studies quantify a statistically significant coefficient for the GDP as the central impact factor on direct commercial real estate returns across the UK (Kohlert, 2010), Finland (Karakozova, 2005) or globally (De Wit & Van Dijk, 2003). The positive relationship between the overall economic development of a country and the corresponding real estate markets is economically obvious. Secondly, unemployment rates are empirically proven to impact direct commercial real estate returns (Liang & McIntosh, 1998; De Wit

& Van Dijk, 2003; Kohlert, 2010). The statistically significant relationship between inflation rates and total returns has been demonstrated empirically by Bond & Seiler (1998), explicitly for the US, abovementioned regions, by Karakozova (2005), Kohlert (2010), De Wit & Van Dijk (2003) and for the UK by Brooks & Tsolacos (1999). With regard to the broader capital market environment, Macgregor & Schwann (2003), Baum (2015), Clayton et al., (2009) and Marcato & Nanda (2016) revealed the statistically significant impact of bond yields on total returns.

Secondly, directly real-estate-related explanatory variables have repeatedly been the subject of empirical studies on commercial direct real estate returns. De Wit & Van Dijk (2003) reveal the statistically significant impact of rental prices on total returns. Other studies confirm these findings with regard to ex ante (Clayton et al., 2009) or ex post (De Wit & Van Dijk, 2003; Karakozova, 2005) rental growth. Since the rental growth is c.p. the central return generating determinant on the income side of a direct property investment, the relationship is economically well-justifiable due to an increased willingness-to-pay of tenants. West & Worthington (2006) contribute to the empirical literature by isolating the relationship between construction activities, or the stock of commercial real estate space respectively, and total returns for an Australian data set. Baker & Saltes (2005) suggest incorporating construction-related sentiment (Architecture Billing Index) into return models. Vacancy rates as a determinant on the demand side, which contributes to total returns, are quantified by De Wit & Van Dijk (2003) at the multi-national level, and by Akinsomi et al. (2018) for South Africa. Hekman (1985) empirically underlines the statistically significant negative relationship between vacancy and rental prices.

Based on the literature review, the hypothesis derivation for the empirical study can be presented. As the primary hypothesis, DEPU is c.p. and on average expected to show a statistically significant negative impact on direct commercial real estate returns. This hypothesis is mainly based on the reductions of appreciation returns due to decreased market agent expectations in ensuing market periods:

Hypothesis 1 – *Domestic economic political uncertainty displays c.p. a timely lagged statistically significant negative impact on European direct commercial real estate returns.*

Secondly, not only domestic or internal political uncertainty affects real estate markets. After controlling for DEPU, GEPU is also a significant factor in determining commercial direct real estate returns. Global macroeconomic integration of real estate markets is the underlying theory for this hypothesis:

Hypothesis 2 – *After controlling for domestic economic political uncertainty, global economic political uncertainty displays a lagged statistically significant negative impact on direct real estate returns in Europe.*

2.3 Research design and measurement of uncertainty

Based on the abovementioned empirically proven determinants of direct commercial real estate returns, the aim of the present study is to isolate the potential impact of EPU on direct commercial real estate returns. EPU proxies generally quantify the exposure of a region to insecurities caused by political events with a potential impact on economic performance. Methodologically, these indices condense information through textual analysis of national newspapers and their relative frequency of using terms that indicate EPU. These indices quantify the level of uncertainty expressed by public media, which is also available to real estate market agents. The typically applied index within the relevant body of real estate literature (e.g. Antonakakis et al., 2015) is the Economic Policy Uncertainty Index (EPUI), introduced by Baker et al. (2011).

The EPUI publishes two different data series. Firstly, a country-level index is published for 20 countries across the globe. This index is used as the study's proxy for the domestic EPUI (DEPUI) [1]. The DEPUI counts native language newspaper articles containing the combination of terms "economy" (E), "policy" (P) and "uncertainty" (U) or similar words as the share of the total number of articles in the same period. Based on this ratio, the calculated value is then normalized by the total number of words and rescaled by multiplying it by 1,000 (based on Davis, 2016). Thus, a higher DEPUI represents a higher level of uncertainty and vice versa. Examples of newspapers in the countries of the data set are *Handelsblatt* and *Frankfurter Allgemeine Zeitung* (Germany), *Le Figaro* and *Le Monde* (France), *The Times of London* and *Financial Times* (UK) or *Corriere Della Sera* and *La Republicca* (Italy).

Secondly, the global EPUI (GEPUI) is calculated as the GDP-weighted national DEPUI scores, which are calculated as described above. The GDP-weighting is in line with logical expectations of economically larger nations exerting a stronger impact on the overall global political environment. The constituents of the GEPUI account for about 70% of the PPP-adjusted global economic output.

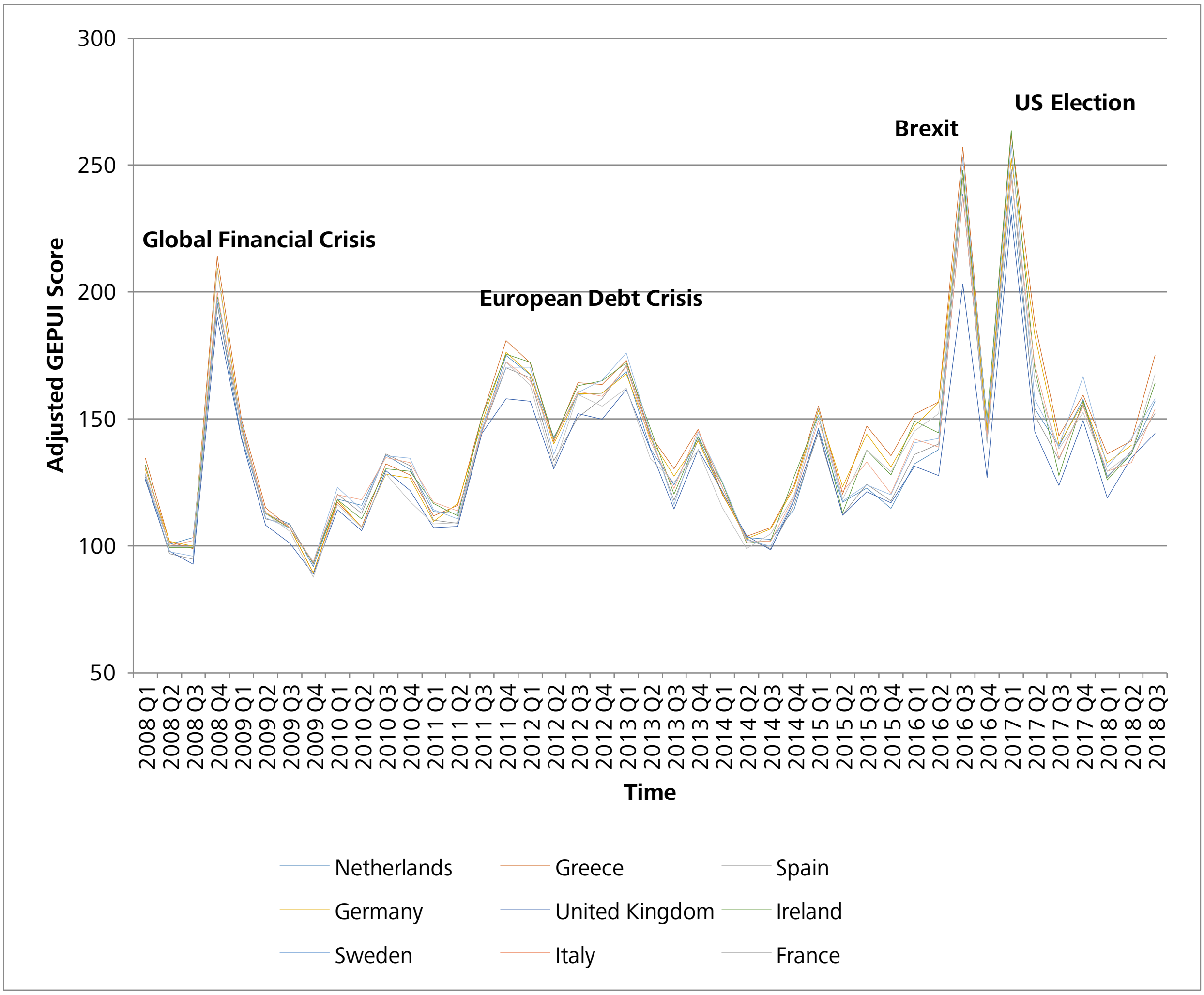
Nonetheless, a decisive methodological adjustment needs to be made at this point. As described, the GEPUI condenses all national EPUI scores into a single figure. Thus, the proxy includes the country's own score as well. This inclusion, however, is inappropriate for the present approach of separating the impact of the GEPU from the DEPU. Therefore, an adjusted GDP-weighted GEPUI is calculated, which is the mean over all other countries (n -1), but explicitly without the country's own score:

$$Adjusted\ GEPUI_{i,t} = \frac{1}{n-1} \sum_{j \neq i}^{n-1} \frac{GDP_{j,t}}{\sum_{k=1}^{n-1} GDP_{k,t}} \times DEPUI_{j,t} \tag{4}$$

In addition, the adjustment of the GEPUI is important for econometric reasons. A missing adjustment causes a missing variation across the individuals of the data set, because the value would be identical for all individuals in the same period. Accordingly, the only variation was across time. Time fixed effects, however, capture exactly the specified variation across time.[2]

In order to assess the sensitivity of the calculated index optically, Figure 1 displays the development of the adjusted GEPUI across time for the European countries of the data set:

Figure 1: Adjusted GEPUI scores (Q1/2008 – Q3/2018)



Source: Own presentation.

[2] The exact econometric specification can be found below in the section "methodology".

The adjusted GEPUI clearly shows spikes in phases of prominent recent political events, which are generally associated with periods of increased political uncertainty, like the global financial crisis in 08/09, the European debt crisis in 11/12, the 2016 Brexit referendum and the election of the 45th President of the US. In sum, due to the extensive coverage of global economic output and clear measurement of political turmoil, the DEPUI and the adjusted GEPUI both appear to be legitimate proxies for DEPU and GEPU.

2.4 Data and descriptive statistics

The panel data covers observations from 20 European cities (n = 20) in 9 countries [2], with quarterly observations for office properties from Q1/08 to Q3/18 (t = 43). The limiting factor for including markets in the data set is the availability of the DEPUI, which needs to be observable for each market in each period.

On the dependent side, total returns represent the variable of interest, because they are a classic and well-known proxy for property investment performance. The total returns were obtained from CoStar. The named data provider aggregated the returns from cash-flows as well as from a repeated-sale regression model, which accounts for potential autocorrelation of the data. In order to isolate the impact of the DEPU and GEPU on the direct total returns of direct real estate investments in Europe, the literature review provides the foundation for the variable selection process of the controls. Here, the empirically proven macroeconomic and real-estate-market-related variables were taken from the literature for similar markets and data sets, in order to construct a robust set of control variables to model the remaining variance of the total returns. The variable selection process needs to be conducted particularly carefully, because macroeconomic models are particularly prone to multicollinearity (see Table 1):

Table 1: Data description and variable selection for total return models

Variable	Description	Proxy for	Level	Source
Total return	The total returns represent the overall appreciation and income return generation of direct real estate investments, as previously used by Akinsomi et al. (2018).	Property Returns	City	CoStar
GDP growth	Among others, Kohlert (2010) or Akinsomi et al. (2018) argue that the GDP is the most dominant indicator of macroeconomic stability of the direct environment and returns. Hence, the models control for economic output by including quarter-on-quarter GDP growth.	Economic stability	Country	OECD
CPI growth	Inflation is included in order to control for price movements with respect to overall market inflation as	Asset price inflation	Country	OECD

	noted by e.g. Bond & Seiler (1998) or Brooks & Tsolacos (1999).			
Unemployment rate	Employment is often perceived as another indicator of economic health and success. E.g. Liang & McIntosh (1998) use the proxy to isolate the effect of labour-market-related return generation.	Labor market and income	Country	OECD
Gov. bond (10 year maturity)	In line with previous literature (e.g. Macgregor & Schwann, 2003; Baum, 2015), the government bond as an indicator of the overall interest level of other investments is incorporated.	Investment environment	Country	OECD
Economic Sentiment Index	In order to distinguish between economic sentiment and EPU, a proxy for the former is introduced (e.g. Tsolacos et al., 2014; Ling et al., 2015). Only by doing so, can the impact of EPU be isolated from the overall economic sentiment.	Economic sentiment	Country	Eurostat
Vacancy	Office vacancy serves as an indication of the current state of demand in a real estate market, so as to isolate the impact of the markets' demand side (e.g. in line with De Wit & Van Dijk, 2003; Akinsomi et al., 2018).	Office demand	City	CoStar
Stock	Stock indicates the available office floor space and therefore shows the size of the market and / or the building activity. It is supposed to control for the office supply, in line with West & Worthington (2006).	Office supply	City	CoStar
Rent growth	Year-on-year rent growth shows the income growth potential of office buildings in the respective market, as proposed by Clayton et al. (2009).	Income expectations	City	CoStar

Source: Own presentation.

Based on this selection of variables, the subsequent univariate analysis provides descriptive information about the data. Firstly, since panel data models may be subject to potential non-stationarity, a unit root test to check for temporal econometric distractions is carried out (see Table 6). The non-stationary covariates were differenced, in order to generate a stationary time series, denoted by Δ(x). Table 2 displays the descriptive statistics for both dependent and independent variables, including the target variables:

Table 2: Descriptive statistics for variables of the total return models

Variable	n	Unit	Mean	SD	Min.	Max.
Dependent Variable						
Total return	860	%	0.016	0.021	-0.092	0.114
Macroeconomic controls						

Avg. Economic Sentiment Index	860	Score	99.589	10.345	64.166	116.067
GDP growth	860	%	0.002	0.010	-0.047	0.099
∆CPI growth	840	%	-0.007	0.868	-0.027	0.031
∆Unemployment rate	840	%	-0.001	0.013	-0.090	0.090
Gov. Bond 10 year maturity	860	%	0.027	0.025	-0.001	0.254
Real-estate-related controls						
Vacancy	860	%	0.107	0.043	0.031	0.255
∆ Stock / 100,000	840	sqm	2.891	3.326	-11.990	20.886
Rent Growth	860	%	0.002	0.022	-0.134	0.126
Target Variables						
DEPUI	860	Score	151.423	80.545	27.632	1141.796
GEPUI	860	Score	140.108	33.798	87.535	263.612

Note: ∆ indicates the first differences of the variable. Thus, these variables contain one observation less per individual. Sqm stands for square meters.

Source: Own presentation.

From the descriptive statistics table, the need for a natural logarithm transformation of multiple variables becomes apparent, because they differ substantially with regard to their absolute values. These variables include the target variables and the economic sentiment indicator. The study incorporates all monetary values in Euros to ensure a consistent currency base across all values in the dataset. In addition to the univariate description of the data set, the correlation matrix is reported below (see Table 3):

Table 3: Correlation matrix of the total return data set

		1	2	3	4	5	6	7	8	9	10	11
1	Total Return	1.000										
2	GDP growth	0.385	1.000									
3	∆CPI growth	0.050	0.053	1.000								
4	∆Unemployment rate	0.044	0.073	0.021	1.000							
5	Gov. bond	-0.456	-0.338	-0.025	-0.148	1.000						
6	Economic Sentiment Index	0.662	0.543	0.176	0.023	-0.532	1.000					
7	Vacancy	-0.211	-0.024	-0.086	-0.280	0.451	-0.212	1.000				
8	∆Stock	0.020	0.009	-0.013	0.144	-0.151	0.005	-0.291	1.000			
9	Rent growth	0.438	0.128	0.027	0.039	-0.172	0.308	-0.171	0.047	1.000		
10	DEPUI	0.131	-0.026	-0.069	0.041	-0.173	0.018	-0.278	0.403	0.039	1.000	
11	GEPUI	0.119	-0.144	-0.093	-0.110	-0.154	0.036	-0.048	-0.025	0.036	0.405	1.000

Note: ∆ indicates the first differences of the variable.

Source: Own presentation.

From the correlation matrix, various insights can be obtained. Most importantly, the matrix displays linear correlations that differ from zero for the dependent variable on one hand and the target variables of interest on the other (DEPUI: 0.131; GEPUI: 0.119). Additionally and from a methodologic point of view, other positive correlation values above 0.25 (in line with e.g. Oertel et al., 2020) are defined as the threshold for econometric issues among the independent controlling covariates to monitor multicollinearity (namely GDP growth, rent growth, vacancy and economic sentiment). Thus, the estimation of a clean relationship between the dependent and the target variable are ensured. Nonetheless, it needs to be highlighted, that the target variables potentially yield information and thus reveal a correlation with other macroeconomic controls.[3] Accordingly, a base model with all variables is estimated, because the variable selection process above suggests the inclusion of all these variables from an economic perspective. However, from an econometric perspective, the variables mentioned above are systematically excluded in order to carry out robustness checks against potential distractions due to the outlined multicollinearity.

2.5 Methodology

The methodological framework is a classic OLS estimation for the described panel data set. Total returns are the dependent variable, and a multivariate model is specified to estimate the parameters for the covariates:

$$\begin{aligned}\text{Total Return}_{i,t} = {} & \beta_{i,t-k} m_{i,t-k} + \beta_{i,t-k} r_{i,t-k} + \beta_{i,t-k}\text{domestic EPU}_{i,t-k} \\ & + \beta_{t-k}\text{global EPU}_{i,t-k} + \beta_t \text{time}_t + \beta_i \text{city}_i + \varepsilon_{i,t}\end{aligned} \tag{5}$$

Here, the dependent total return observed in a market i in quarter t is a function of the abovementioned domestic macroeconomic controls captured in vector $m_{i,t-k}$, and real-estate-related variables in the vector $r_{i,t-k}$. More importantly, the scalars $\text{domestic EPU}_{i,t-k}$ and global EPU_{t-k} yield the proxies for the variables of interest:

$$m_{i,t-k} = \begin{cases} \ln(\text{Economic Sentiment}) \\ \text{GDP growth} \\ \Delta(\text{CPI growth}) \\ \Delta(\text{Unemployment rate}) \\ \text{Gov. Bond 10 yr maturity} \end{cases} \tag{6}$$

$$r_{i,t-k} = \begin{cases} \text{Vacancy} \\ \Delta(\text{Stock}) \\ \text{Rent growth} \end{cases} \tag{7}$$

[3] The orthogonalization of the relationship can be an alternative methodological approach to separate the information from the target variable and the control set.

$$\text{domestic EPU}_{\mathrm{i,t-k}} = \ln\text{(DEPUI)} \tag{8}$$

$$\text{global EPU}_{\mathrm{i,t-k}} = \ln\text{(adjusted GEPUI)} \tag{9}$$

Since there may be temporal heterogeneity of returns, dummy variables labeled as time for each year of the sample are incorporated (base = 2008). City heterogeneity is captured throughout all models by including city dummies (as noted by Monfared & Pavlov, 2019). Frankfurt is chosen as the reference, because of its geographic centrality, and $\varepsilon_{i,t}$ represents the error term for each specification.

Furthermore, the relationship between non-fundamentals and direct real estate returns are known for their lagged effects (Case & Shiller, 2003; Case et al., 2014). Accordingly, each model contains lagged terms up to the fourth quarter for the covariates (k = 4, in line with Antonakakis et al., 2015).

An additional remark needs to be made concerning the potential autocorrelation of the dependent variable. In order to account for potential autocorrelation, literature has repeatedly used vector autoregressive models (e.g. Clayton et al., 2009). However, since the present study uses a ML-based OLS estimation in line with Akinsomi et al. (2018), it needs to be highlighted, that the data uses transaction-based capital value returns. In contrast to appraisal-based appreciation, these returns generally do not suffer from appraisal smoothing due to anchoring (in line with Geltner et al., 2003). Therefore, no autoregressive component is added.

2.6 Empirical results

The results for the OLS models can be found below (see Table 4). The base model in the first column includes all control variables, which were identified above in related studies as important determinants of the total returns. The subsequent models individually exclude the variables of GDP growth, rent growth, vacancy and the economic sentiment index, so as to check for econometric robustness of the beta coefficients of the target variables. The specified variables were systematically exchanged, due to the reported correlation findings. From an economic point of view, the first column displays the central and most important econometric models, containing all relevant controls. Subsequent models are used to conduct various robustness checks.

The models 2.x are specified to assess the second hypothesis regarding the impact of the GEPU. Here, the DEPUI scores are considered to be part of the control variables in addition to the remaining controls of the base model specification. The models are then extended by the adjusted GEPUI scores.

Table 4: Pooled OLS estimation results (total return)

	Dependent variable: Total Return									
Model	Model 1	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 2	Model 2.1	Model 2.2	Model 2.3	Model 2.4
Controls:										
Macroeconomic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Real estate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded control	None	GDP growth	Rent growth	Vacancy	Sentiment	None	GDP growth	Rent growth	Vacancy	Sentiment
Target variables:										
DEPUI	-0.0002	-0.003	-0.003	-0.002	-0.002	-0.004	-0.005	-0.003	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DEPUI (-1)	-0.002	-0.002	-0.003	-0.002	-0.002	0.002	-0.002	-0.004 ***	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DEPUI (-2)	-0.003 ***	-0.003 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.003 ***	-0.003 **	-0.004 ***	-0.003 **	-0.003 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
DEPUI (-3)	-0.003 ***	-0.003 ***	-0.004 ***	-0.004 ***	-0.004 ***	-0.003 **	-0.003 **	-0.003 ***	-0.003 **	-0.003 **
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DEPUI (-4)	-0.002 **	-0.002 **	-0.004 **	-0.002 ***	-0.002 ***	-0.003 ***	-0.003 ***	-0.004 ***	-0.004 ***	-0.004 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Adjusted GEPUI						0.005	0.004	0.008 ***	0.005	0.0001
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adjusted GEPUI (-1)						0.002	0.003	0.003	0.003	0.0002
						(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Adjusted GEPUI (-2)						0.002	0.002	0.003	0.003	-0.0005
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Adjusted GEPUI (-3)						0.004	0.004	0.005	0.006 **	0.005
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adjusted GEPUI (-4)						0.008 ***	0.008 ***	0.010 ***	0.010 **	0.008 ***
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.140 ***	-0.099 ***	-0.303 ***	0.090 ***	-0.009 ***	-0.276 ***	-0.238 ***	-0.490 ***	-0.368 ***	0.031
	(0.056)	(0.049)	(0.065)	(0.014)	(0.014)	(0.075)	(0.067)	(0.082)	(0.079)	(0.036)
Observations	760	760	760	760	760	760	760	760	760	760
Adjusted R^2	0.766	0.764	0.702	0.722	0.753	0.767	0.767	0.707	0.726	0.755

Notes: The estimations are based on pooled OLS panel regressions with year and city dummies. "(-t)" denotes the t-th lag of the covariate. The estimation results of the control variables are available upon request. Dummies are included but not reported. Heteroscedasticity and autocorrelation-robust standard errors were used. ***, ** and * represent statistical significance at 0.01, 0.05 and 0.10 levels, respectively. Standard errors are displayed in parentheses.

Source: Own presentation.

With regard to the overall explanatory power of the econometric models, the results generally yield adjusted R^2 values around 0.75 – 0.80 for the total returns, which are in line with those in the literature (e.g. recently from Akinsomi et al., 2018). The potential threat of omitted variable bias is sufficiently accounted for, because the explanatory power of the models of the present study yields similar results to existing equivalent studies. Heavy distractions from omitted variables in the control variable set are unlikely to be present. The incremental value of the newly added variables cannot be extracted directly from Table 4. Therefore the same models as above are estimated, but without the DEPUI and GEPUI variables. By doing so, it is possible to show differences in explanatory power of the models without the targets and thus show the incremental value of the newly added target variables (see Table 5):[4]

Table 5: Explanatory power of total return models without DEPUI / GEPUI

Model	Model 1	Model 1.1	Model 1.2	Model 1.3	Model 1.4
Controls:					
Macroeconomic	Yes	Yes	Yes	Yes	Yes
Real estate	Yes	Yes	Yes	Yes	Yes
Excluded control	None	GDP growth	Rent growth	Vacancy	Sentiment
Observations	760	760	760	760	760
Adjusted R^2	0.757	0.755	0.685	0.714	0.742

Source: Own presentation.

As displayed on Table 5, the explanatory power of the models without the DEPUI and the GEPUI reveal lower adjusted R^2 values for all specifications in comparison to the models reported above. Thus, the introduction of the DEPUI provides an initial value in explanatory power for the modelling of total returns. Since the explanatory power of the models with the GEPUI is again higher than the models including only the DEPUI, the incremental value for both variables can be confirmed (see Table 4). However, the deltas of the explanatory power values between the models, including the GEPUI proxy and those excluding the specified variable are limited. Thus, general statistical significance can be observed, whereas the low explanatory power of the GEPUI proxy needs to be acknowledged.

Turning to the individual coefficients, the empirical results show c.p. on average a statistically significant negative impact of all lags between the second and fourth period on the DEPUI and the total returns across all specifications. The beta coefficients for the DEPUI reveal a range between -

[4] Estimates for the beta coefficients are explicitly not reported, because these are of minor interest only. In order to isolate the incremental value of the estimates for the DEPUI and GEPUI, however, the explanatory power of the models is sufficient.

0.003 and -0.004. Since the target variables are transformed by a natural logarithm and the index is denoted in a number and the total returns in percentages, the c.p. interpretation of the estimated coefficients is as follows. A one unit increase in DEPUI results on average, c.p. in a decrease in total return of -0.003 – (-0.004) % and vice versa, because the total returns are denoted on a decimal scale.[5] Accordingly, the marginal effect needs to be divided by 100, whereas the recalculation from decimal figures to percentages requires the multiplication by 100. Thus, the coefficient can be interpreted as it is reported in the regression output. The relatively small magnitude of the marginal effect is also as expected, because the fundamental determinants such as GDP growth etc. are assumed to be the dominant impact factors. With regard to the first hypothesis, there is no empirical proof for falsification. In fact, the results support the idea of a c.p. performance lowering effect of increased DEPU, and vice versa.

Nonetheless, the empirical results reveal a statistical significant negative relationship between the DEPUI and total returns. This finding is somewhat puzzling, because the correlation matrix showed a positive correlation between total returns and the DEPUI variable. In this context, a methodological remark needs to be made. The Pearson correlation coefficient identifies a linear relationship between two variables without an *a priori* assumption of direction. The beta coefficients on the other hand estimate the linear relationship between a dependent and an independent variable, explicitly given other impact factors. Especially for a non-fundamental factor such as the DEPU, there is no economic justification for an impact without other controlling variables. Thus, the significance of the correlation coefficient is severly limited. Other and most importantly, fundamental impact factors, need to be included in total return models. These models have to be analyzed as a whole and with an economically justified specification of a joint impact pattern.[6]

Secondly, the extended models, which also include the adjusted GEPUI score, yield robust statistically significant contrary signs for the total returns, predominantly in the fourth lag. Here the beta coefficients show betas of 0.008 – 0.010. A change in one unit of the GEPUI results on average, c.p. to a positive change of 0.008 – 0.010 %, and vice versa.[7] Interestingly, the betas are larger than for the DEPUI. Thus, the individual strength of effect of the GEPUI is larger than for each of the lags of the DEPUI. In sum, it can be stated that increasing uncertainty in foreign countries supports the performance of domestic commercial properties. This finding provides evidence for the existence of a potential "safe haven effect", namely the performance boost of domestic properties in phases of

[5] Accordingly, an increase in 100 points in DEPUI for example leads to 0.3 - 0.4% or 30 - 40 base points total return, and vice versa.
[6] The justification for the present specification is presentedabove in the section "Data and descriptive statistics".
[7] In line with the interpretation of the DEPUI, a rise of 100 points in GEPUI leads to an increase of 0.8 – 1.0 % or 80 – 100 base points, and vice versa.

elevated foreign EPU. For other lags, the statistical significance of coefficients is not robust across the model variations. Besides the statistical significance, especially for the contemporary coefficient of the GEPUI, the economic significance is questionable. A direct effect in the same period is economically problematic, because market agents are expected to price uncertainty in later periods, as mentioned by Case & Shiller (2003) or Case et al., (2014).

The abovementioned expectations of a negative impact of GEPU on domestic commercial real estate returns or the second hypothesis can thus be falsified. Instead, the results are in line with those findings from the residential sector, which reveal c.p. a positive relationship between total returns and GEPUI. An increase in demand by domestic as well as foreign market agents for local properties constitutes a credible channel for commercial properties.

2.7 Conclusion and further remarks

This study presents a new approach to explaining the relationship between EPU and direct commercial real estate returns in an OLS framework for a panel data set. The study reveals the impact of DEPU and GEPU on total returns of major European commercial property markets. The main finding is that on the one hand, DEPU shows c.p. on average a lagged statistically significant negative effect on total returns, whereas GEPU has c.p. a positive impact on the total returns of domestic properties.

Thus, GEPU does not directly transmit a negative effect from foreign countries to commercial real estate returns into another country. Thus, the potential for spillover effects, as outlined in the macroeconomic literature, cannot be confirmed for commercial real estate markets. Instead, the results of the present study confirm the empirical findings of previous articles referring to a "safe haven effect" (e.g. Badarinza & Ramadorai, 2018). Nonetheless, for both parts of the EPU, the impact is much smaller than for the fundamental impact factors, as can be extracted from the incremental values of the models without the DEPUI and the GEPUI (as reported on Table 4 & 5).

The transmission channels from EPU to the total returns are yet to be quantified empirically. This applies to the DEPU as well as the GEPU. The theoretical background underlines the importance of the appreciation side as main driver for the EPU to influence total returns, as discussed in the literature review. However, the exact channels, especially for the GEPU and the "safe haven effect", remain uncertain and should be subjected to further investigation. Cross-border investments may be a plausible transmission channel in this context. Since potential additional foreign demand could explain increased total returns, an subsequent empirical study on cross-border capital flows as a function of political uncertainty, appears to be promising. A statistically significant, c.p. and on average positive impact of GEPU on cross-border capital flows was the logical working hypothesis for assessing the transmission channel.

Additional research could also be conducted on other usage types. In this context, especially logistic properties may be of interest, since the asset class is known for its heavy dependency on global trade and the political stability of international economic linkages (Boutchakova et al., 2012). A potential proxy for quantifying the impact of trade-related political uncertainties could be the Trade Policy Uncertainty (TPU) Index from the Federal Reserve Board. Lastly, future research could integrate the bodies of literature on different measures of EPU (for a broader discussion, see Ghirelli et al., 2019) with machine learning approaches such as Braun et al. (2019). A potentially beneficial outcome could be machine-learning-based EPU indices that learn dynamically to adjust the textual tone of the underlying dictionary.

Some practical implications can be derived especially for the risk management of investors from a corporate point of view, as well as for political stakeholders from an administrative perspective. The present study underlines the importance of monitoring the political environment, both domestically and globally, since they represent statistically significant drivers of direct commercial property returns. Thus, risk surveillance procedures should be implemented to monitor the political environment of the assets, especially regarding the potential acquisition of properties in regions of elevated DEPU. This would be especially fruitful, because the study reveals a timely lagged impact pattern. Thus, investors could gain a competitive advantage over other market participants who do not monitor the political environment due to the correct anticipation and pricing of EPU-related risk. A possible specific implementation could be an early warning system, which tracks the development of the political environment in order to predict potential downturns in future total returns. In combination with the abovementioned machine-learning-based future research, a joint approach to construct an early warning system based on dynamic learning algorithms could be the best practice for applied risk management in real estate to anticipate downturns. For political stakeholders, the results should increase their awareness of the potentially negative impact of uncertainty-inducing statements. By contrast, the use of risk-averse communication of administrative personnel may protect domestic real estate markets by decreasing the EPU of the news media landscape.

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2.9 Appendix

Table 6: Levin-Lu-Chu stationarity test for total return model variables

Variable	Test statistic	P-Value	Variable with Δ	Test statistic	P-Value
Dependent Variables					
Total return	-2.026	0.021			
Macroeconomic variables					
GDP growth	-8.509	0.000			
CPI growth	2.817	0.998	CPI growth Δ	-20.714	0.000
Unemployment rate	17.571	1.000	Unemployment rate Δ	-237.348	0.000
Gov. Bond 10 yr. maturity	-3.435	0.000			
Real-estate-related variables					
Vacancy	-6.534	0.000			
Stock	-0.390	0.348	Stock Δ	-3.003	0.001
Rent Growth	-12.858	0.000			
Target Variables					
DEPUI	-18.964	0.000			
GEPUI	-5.247	0.000			

Note: Δ indicates the first differences of the variable. The maximum lag was set to 4, since our maximum time lag within the econometric model is equals to 4.

Source: Own presentation.

3 Do Cross-Border Investors Benchmark Commercial Real Estate Markets? Evidence from Relative Yields and Risk Premia for a European Investment Horizon

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Journal of European Real Estate Research, 13(1) (published)

Abstract

The purpose of the study is to introduce a new perspective on determinants of cross-border investments in commercial real estate, namely the relative attractiveness of a target market. So far, the literature has analyzed only absolute measures of investment attractiveness as determinants of cross-border investment flows. The empirical study uses a classic OLS estimation for a European panel data set containing 28 cities in 18 countries, with quarterly observations from Q1/2008 – Q3/2018. After controlling for empirically proven explanatory covariates, the model is extended by the new relative measurement based on relative yields/cap rates and relative risk premia. Additionally, the study applies a generalized additive mixed model, to investigate a potentially nonlinear relationship. The study finds on average a c.p., statistically significant lagged influence of the proxy for relative attractiveness. Nonetheless, a differentiation is needed; relative risk premia are statistically significant, whereas relative yields are not. Moreover, the generalized additive mixed model confirms a nonlinear relationship for relative risk premia and cross-border transaction volumes.

3.1 Introduction

Direct cross-border investments in commercial properties have increased steadily over the past two decades. Accordingly, the related research and market participants have demonstrated an increased interest in understanding the determinants of capital flows across national borders.

Institutional economics theory defines the attractiveness of a target investment market as a function of its socio-economic environment and institutional framework (Fuerst et al., 2015). In line with this theory, Lieser & Groh (2014) provided empirical evidence of the importance of economic growth, demographics, urbanization or political stability of a particular country. However, other authors highlight the importance of additional factors on cross-border capital flows. Yet, the literature has described the attractiveness of an investment location solely with absolute measures of potential determinants.

The present article introduces a new approach to explaining inflowing cross-border capital into real estate market, namely *relative* attractiveness. As opposed to previous studies, it sheds light on whether cross-border investors benchmark investment opportunities against each other. More precisely, the study investigates whether relative attractiveness in the form of relative yields or relative risk premia determines the capital allocation of investors. In this context, the analysis concentrates on European real estate markets, as classic prime European investment markets represent rather homogenous, substantially economically integrated and geographically densely located competing investment markets. Thus, relative attractiveness appears to be a potential driver, but solely for geographical reasons. At the same time, as outlined by Devaney et al. (2017a), data availability issues in Europe especially at the city level have hampered research on cross-border transaction activity. Consequently, work at this level requires new empirical evidence.

The paper is structured as follows: A comprehensive literature review builds the foundation for the empirical study. The essence is the existing body of literature on the one hand, while legitimating the approach of introducing relative attractiveness as a further driver of cross-border investment activity on the other. The section concludes with a statement of the hypotheses for the empirical work. Subsequently, the paper outlines the data set and research design, including the new target variables for measuring the relative attractiveness of a city. It also reports the descriptive statistics. Since macroeconomic models on cross-border investment activities in real estate markets are subject to severe methodological challenges and data availability issues, the variable selection process and the econometric approaches are discussed extensively. Afterwards, the empirical results are presented, and some conclusions drawn.

3.2 Related literature and hypotheses derivation

Several studies have tried to identify common determinants of cross-border real estate investment in the view of various investor types and investment styles. From a portfolio point of view, national and regional diversification benefits are often perceived as one of the driving forces behind international capital allocation in real estate. Amongst others, Sirmans & Worzala (2003) and Holsapple et al. (2006) argued that the diversification of country-specific economic drivers is decisive. The abovementioned literature on diversification, however, often suffers from data unavailability on investors who cause the transaction flows. Thus, the relationship between investor, relevant portfolio and investment flow cannot be established. Accordingly, a growing body of literature has focused on investor-unrelated and general institutional and macroeconomic determinants of cross-border investment flows. Hence, several studies have investigated investment drivers and barriers on global and regional levels.

A comprehensive empirical study on the economic and institutional environment was conducted by Lieser & Groh (2011). First, they defined six relevant areas for cross-border investments, namely economic activity, real estate investment opportunities, the depth and sophistication of capital markets, investor protection and the legal framework, administrative burdens and regulatory limitations, as well as the socio-cultural and political environment. In a second step, they quantified the attractiveness of countries via a composite index approach. In a second paper, Lieser & Groh (2014) analyzed which of these country characteristics impact on foreign real estate investment volumes. After investigating 47 countries, they illustrated a significant relationship between foreign real estate investment activity as the dependent variable and real estate investment opportunities, the depth and sophistication of capital markets, investor protection and the legal framework, administrative burdens and regulatory limitations as explanatories. In line with this study, Devaney et al. (2017a) found that in European and Asian Pacific countries, the size and wealth of a country, the specific country risk, and property rights, as well as the performance of the real estate markets, mainly determine transaction activity.[8]

A second stream of papers narrowed the geographic focus and carried out empirical studies on national or city-level determinants. Chin et al. (2006) and Pi-Ying Lai & Fischer (2007) identified patterns in Asian regions and cities. They highlighted that political stability and legal regulations, as well as sound financial and economic structures, and the strength and stability of the current economy, are of major importance for investments in these areas. He & Zhu (2010) added that aside

[8] Transaction activity was measured from turnover rates of the total transaction volume taking foreign and domestic investments together.

from a favorable institutional environment, Chinese cities and their real estate markets attract capital through population and market size. For Eastern Europe, McGreal et al. (2001) argued that foreign real estate investment activity can be affected negatively, especially by non-transparency, overall economic conditions, corruption, and bureaucracy. Salem & Baum (2016) found that foreign money flows into real estate markets in the Middle East and northern African countries are mainly influenced by political stability. Devaney et al. (2017b) investigated transaction activity in U.S. metropolitan office markets. Economic growth and market size were positively related to turnover rates, whereas vacancy rates and risk showed a negative relationship.

The studies presented thus far indicate that the institutional framework and the macroeconomic conditions shape cross-border investment. However, real-estate-related factors also influence cross-border capital flows, since investment success is not only linked to country characteristics, but also to the underlying real estate market and the property itself. A number of authors have therefore included various proxies of real estate markets into their investigations. Ford et al. (1998) found that market activity and rent levels of US real estate markets determine foreign investment behavior. Moreover, according to Laposa & Lizieri (2005) office construction attracts foreign investment in Eastern Europe. For China, He and Zhu (2010) showed that aside from satisfactory demographic conditions, already invested foreign capital attracts both foreign developers as well as more cross-border investors. In addition, Rodríguez & Bustillo (2010), Gholipour Fereidouni & Ariffin Masron (2013) and Farzanegan & Fereidouni (2014) observed market-specific property prices to be influential. Interestingly, Gholipour Fereidouni & Ariffin Masron (2013) found real estate market transparency to be an important determinant for foreign investors, but Farzanegan & Fereidouni (2014) did not confirm this finding. Fuerst et al. (2015) established a positive relationship between market liquidity and cross-border capital inflows, since the ability to sell properties increases. Devaney et al. (2017a) noted a negative relationship between office vacancy rates and turnover rates. With particular respect to property characteristics, Devaney et al. (2018) demonstrated that cross-border investors in U.S. gateway cities favor large and new buildings close to CBD locations.

To gauge investment potential and to explain capital flows, risk characteristics such as the previously documented institutional, macroeconomic and real estate related variables constitute crucial considerations. Nonetheless, income opportunities, which may additionally influence investors, can be assessed by analyzing yields and pricing. A common method of early real estate investment evaluation is the capitalization (cap) rate. It is usually computed as the ratio of a property's net operating income to its price and therefore serves as an opportunity to compare assets and markets. When assessing the main determinants of cap rates, the literature refers to the Gordon-growth model (see e.g. McAllister & Nanda (2016a)):

$$Capitalization\ Rate = Nominal\ risk\text{-}free\ rate + \ Risk\ premium\ - \ Income\ growth \quad (10)$$

The nominal risk-free rate is often approximated by a long-term government bond, whereas the risk premium marks the difference between the government bond and an individual asset yield. The income growth measures the growth of rents or net operating income. Research companies, brokers and other market participants regularly provide cap rates and therefore enable investors to measure and compare investment potential. To the best knowledge of the authors, only a little research has investigated the cap rate/yield and investment flow relationship, even though a direct relationship between both seems reasonable.

With respect to foreign investment, McAllister & Nanda (2016a) and Oikarinen & Falkenbach (2017) detected that foreign capital decreases cap rates. For the present study, the subsequent question of whether the reverse relationship holds true and that cap rates impact investment activity has barely been analyzed. Considering American real estate, Ford et al. (1998) argued that foreign investors react to changes in cap rates. Considering turnover rates in international office markets, Devaney et al. (2019) could not prove that cap rates influence general investment activity. To shed more light on this topic, we suggest a new approach to analyzing cap rates and cross-border flow dynamics. So far, potential and actual determinants in the literature were taken into account in order to display the absolute attractiveness of real estate markets. However, we are interested in whether cross-border investors not only look at specific market characteristics representing the absolute attractiveness, but also benchmark certain key determinants such as yields and specifically cap rates against neighboring and competing markets.

More precisely, when cross-border investors choose among target locations, we expect them to look for outperformance opportunities within a predefined investment horizon. Thus, investors search for relative attractiveness among a given set of markets at the time of deploying capital. A straightforward way to evaluate outperformance is to benchmark key metrics such as yields and risk compensation. Therefore, the present study analyzes empirically whether cap-rate-based relative yields and relative risk premia contribute to the relative attractiveness affecting cross-border investments. This leads to the first hypothesis:

Hypothesis 1: *The relative attractiveness of real estate markets affects cross-border capital inflows.*

The vast majority of the abovementioned articles use classic linear models, based mainly on panel models and OLS estimations. The present study aims at contributing to the existing body of literature by relaxing the assumption of a constant effect of the explanatory variables on cross-border investment volumes, as proposed by Devaney et al. (2017a). Possible reasons are potential investor heterogeneity with regard to risk appetite, differences in funding and investor herding behavior. Inspired by the real estate literature on hedonic pricing models (Cajias & Ertl, 2018), the present paper uses a generalized additive mixed model (GAMM). Accordingly, a potential nonlinear relationship between the variable of interest and the dependent variable will be assessed, addressing the following hypothesis:

Hypothesis 2: *The relative attractiveness of real estate markets has a nonlinear relationship with cross-border capital inflows*.

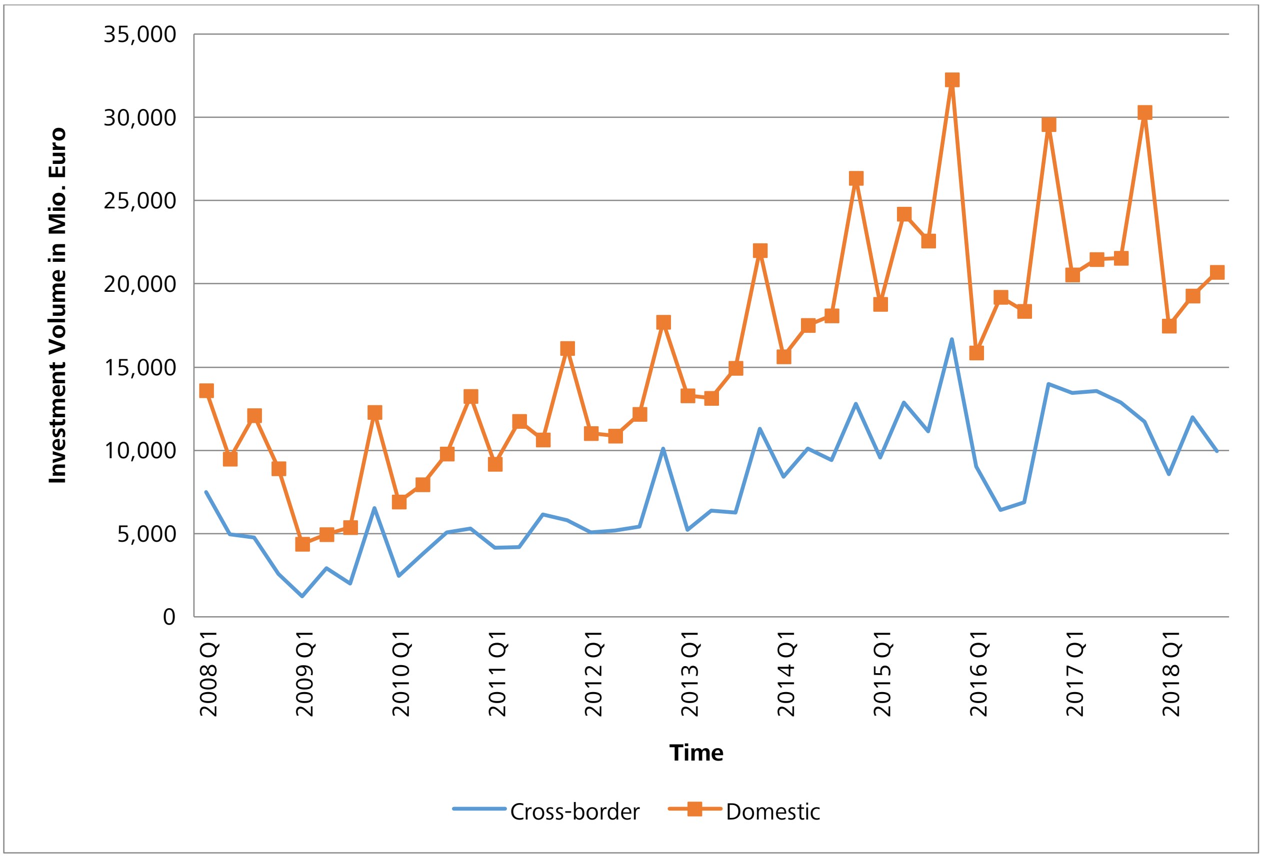
In order to provide insight into the abovementioned hypotheses, the following sections describe the data and the applied methodology. Subsequently the empirical results are presented, which lay the foundation for the assessment of hypotheses. The latter is stated in the conclusion section.

3.3 Data, sample description and methodology

The analyzed data sample contains 28 European cities (n = 28) across 18 countries,[9] with quarterly observations of transaction volumes for office properties from Q1/2008 to Q3/2018 (t = 43). The data is from various data providers. The dependent variable covers quarterly aggregated cross-border transaction volumes of office buildings provided by Real Capital Analytics, Inc. (RCA). RCA is a data-specialist that tracks commercial real estate transactions worldwide including single properties, portfolios and units which mainly consist of commercial real estate. The company applies a standard price floor of 5 Mio. EUR or greater in Europe to consider them in its statistics. Moreover, it sources information about transactions from a variety of investors, brokerage firms, media companies and others. RCA labels a transaction as “foreign” or “cross-border” if the buyer’s or the major capital partner’s headquarter is not situated in the same country as the property. The buyers typically consist of institutional (equity and pension funds, insurances, banks, etc.), listed (REITs, REOCs and listed funds) and private investors (high net worth individuals, non-traded REITs, developers, owners and operators) as well as others (governments, corporates, non-profit, educational and religious users).

[9] The cities in the panel are Amsterdam, Barcelona, Berlin, Brussels, Budapest, Cologne, Copenhagen, Dublin, Dusseldorf, Frankfurt, Gothenburg, Hamburg, Helsinki, Lyon, Madrid, Malmo, Moscow, Munich, Oslo, Paris, Prague, Rome, Stockholm, Stuttgart, Vienna, Warsaw, London and Zurich. As the capital of Russia, Moscow is the only city in the sample outside central Europe.

Figure 2: European commercial real estate investment volume in Mio. Euro (Q1/08 – Q3/18)



Source: Own representation.

Figure 2 depicts quarterly investment volumes of cross-border and domestic investors in the European sample over the course of Q1/2008 to Q3/2018. A visual inspection indicates a positive correlation of both capital types showing a trough in Q1/2009 and a peak in Q4/2015. However, the domestic volumes are continuously greater than the cross-border ones.

The use of RCA data itself is increasing in the real estate literature. Nonetheless, with respect to the measurement of investment activity, there is a debate on what constitutes the right measure to incorporate these flows into econometric models. Devaney et al. (2017b) argue that pure transaction volumes can be driven not only by activity, but also by price inflation. Instead, they suggest turnover rates measured as the appropriate value of the traded properties purchased by domestic and foreign investors, divided by the value of all properties in the market, so as to more accurately capture investment activity. We cannot follow this procedure, since the information on how much of the value of all properties in the market belongs to foreign investors is not accessible. Instead, we stick to the common transaction volumes, but control for inflation to counter the price effect.

Since we aim at replicating average investor behavior, the markets specified in the panel data set appear to be the key ones for global investors looking for investment opportunities in Europe (PricewaterhouseCoopers & Urban Land Institute, 2019). However, a decisive methodological point needs to be highlighted: By defining the panel data set as such, we model the included cities across Europe as a closed investment horizon in which only the markets specified compete for inflowing capital. Thus, the relative attractiveness relates to the benchmark of these investment locations only, assuming other markets beyond this horizon to be irrelevant for cross-border investors. However, the study expects these investors predominantly to target the specified main investment markets.

Since investors typically compare different capitalization potentials of real assets when looking for investment opportunities, ex ante yields form the base of relative attractiveness. The term *relative* indicates the comparison of one market with all others in the sample, which essentially creates a benchmark. To describe the relative attractiveness, we decide to measure the impact of two variables on the aforementioned foreign capital flows: relative yields as well as relative risk premia. The formula is thereby based on the relative return measure of MSCI (2019), which is frequently used, for example, in performance analysis. As the first variable, the relative net mean yield ($RNMY_{i,t}$) is defined as follows (see equation 11):

$$RNMY_{i,t} = \left(\frac{1 + \ PY_{i,t}\left(1 - CIT_{i,t}\right)}{1 + \frac{1}{n}\sum_{i=1}^{n} \ PY_{i,t}\left(1 - CIT_{i,t}\right)} - 1 \right) * 100 \tag{11}$$

$PY_{i,t}$ denotes the prime yield of best located assets in city i for period t.[10] The data stem from CoStar. Additionally, $CIT_{i,t}$ stands for the average corporate income tax of the respective country, obtained from the OECD. The taxation is additionally introduced, since the yield of an investment will eventually be capitalized as a return and thus taxed. The domestic net yield in the numerator is calculated by multiplying $PY_{i,t}$ by one minus the specified tax. Although taxation issues are often neglected in related studies, we incorporate them in order to account for taxation-driven investment decisions, and so the focus is on net yield.[11] The denominator provides the average net yield, which

[10] Although our sample presumably includes not only core investors, we do not consider average yields or cap rates. Instead, we use prime yields since they are from a cost and effort perspective relatively easy to obtain in early market research. Cross-border investors have higher search costs (see McAllister and Nanda, 2016b), suggesting that prime yields offer an inexpensive way to obtain an early market indication. In addition, several practitioners informed us that prime yields are often included in order to assess investment potential in foreign markets.

[11] Yet, we are aware of the fact that especially in Europe certain fund and firm structures prevent taxation payments for real estate investments. Since we do not know which structures are implemented in the analyzed transactions, we include corporate income taxes in our models. Still, the results remained robust without taxes.

is defined by the mean of the $RNMY_{i,t}$ across all individuals. Thus, the denominator can also be interpreted as the abovementioned benchmark. Excess attractiveness of a city in comparison to the mean is c.p. expected to trigger inflowing capital.

Whereas a relative yield benchmarks the sole real-estate-related income potential, investors may be also affected by how much related risk premium a real estate market offers as an excess in relation to the country-specific risk-free alternative. In other words, is there an excess yield, justifying the capital allocation in a property market? Since investors expect risk premia when allocating capital to a risky asset, we specify the relative net mean risk premium ($RNMRP_{i,t}$) as such:

$$RNMRP_{i,t}^{GOV(5|10)} = \left(\frac{1 + (PY_{i,t}\left(1 - CIT_{i,t}\right) - GOV_{i,t})}{1 + \frac{1}{n}\sum_{i=1}^{n} PY_{i,t}\left(1 - CIT_{i,t}\right) - GOV_{i,t})} - 1 \right) * 100 \qquad (12)$$

The nominal risk free rate is approximated by long-term country-specific government bonds. To account for different investment horizons, we include 10 year government bonds to obtain long-term and 5 year government bonds for medium-term risk premia. The bond data is from Thomson Reuters Datastream. For both variables, the calculation works as follows: if Amsterdam's net domestic yield or risk premium respectively was 4.5% in Q2/2013, and the European mean was 4.0% in that quarter, the city's relative attractiveness was 0.4% times 100 above the benchmark, which equals 4.0 in the data set.

In summary, the numerator of the two target variables represents a city's absolute attractiveness. The denominator denotes the constructed benchmark. For both relative attractiveness measures, a ratio above (below) 0 shows relative more (less) attractiveness in the respective city than can be found on European average. The expected signs for both measures of relative attractiveness are positive.

The remaining covariates are macroeconomic and real-estate-related controls, which are in line with the literature described above. In the estimation procedure, all controls are considered in absolute values (e.g. the GDP growth is measured by the value of the country itself), meaning that the relative form only applies to the relative attractiveness measurements. Table 7 summarizes the macroeconomic and real estate controls.

Table 7: Control variable description for cross-border volume models

Variable	Description	Proxy for	Level	Source
GDP growth	Amongst others, Lieser and Groh (2014) argue that a sound and healthy economy is a driving factor for direct real estate investments. Hence, we control for economic stability by including quarter-on-quarter GDP growth in the econometric analysis.	Economic stability	Country	OECD
CPI growth	Inflation is added in order to control for price movements with respect to cross-border transaction volumes. Consequently, quarter-on-quarter CPI growth serves as a control variable that adjusts for changes in the dependent variable due to market conditions.	Asset price inflation	Country	OECD
Unemployment rate	Employment is often perceived as another indicator of economic health and success. Fuerst et al. (2015) state that foreign investors are attracted by good employment conditions. Thus, we use the unemployment rate to capture the labor market and income situation.	Labor market and income	Country	OECD
Global Competitiveness Index (GCI)	In line with previous literature, a condensed country risk measure is central when choosing among international investment opportunities. We decide to control for country risk by using the GCI. The construction of the index is based upon twelve core areas, which cover e.g. institutions, infrastructure, the adoption of information and technologies and others (World Economic Forum, 2018).[12]	Country risk	Country	World Economic Forum
Vacancy	Office vacancy serves as an indication of the current state of demand in a real estate market. According to Devaney et al. (2017b) vacancy captures conditions in the space market.	Office demand	City	CoStar
Stock	Stock indicates the available office floor space and therefore shows the size of the market and / or the building activity. We incorporate it to control for the office supply.	Office supply	City	CoStar
Prime rent growth	Year-on-year prime rent growth shows the income growth potential of prime office buildings in the respective market.[13]	Income expectations	City	CoStar

Source: Own presentation.

The following section reports the univariate analysis for the abovementioned constituents of the data set. Table 8 displays the descriptive statistics of the dependent and target variables as well as the covariates.

[12] Some researchers such as Devaney et al. (2017b) use government and or corporate bonds spreads to control for country risk. To avoid multicollinearity, we cannot include this proxy, since the second target variable relative risk premium is constructed based on government bonds. Additionally, the JLL Global Real Estate Transparency Index series may be an alternative proxy to control for country specific risk factors. Nonetheless, the specified index was not used, because the study incorporates a macroeconomic index to account for effects on a broader and national economic level.

[13] We also controlled for non-prime rent growth. The results stayed robust, but were not reported.

Table 8: Descriptive statistics for variables of the cross-border transaction volume models

Variable	n	Unit	Mean	SD	Min.	Max.
Dependent Variable						
Cross-border transaction volume	1204	T €	277,195	705,530	0	7,384,621
Macroeconomic variables						
GDP growth	1204	%	0.298	0.957	-6.842	9.928
CPI growth Δ	1176	%	-0.007	0.868	-5.035	4.575
Unemployment rate Δ	1176	%	-0.045	1.192	-8.997	8.996
Global Competitive Index	1204	Index	5.168	0.439	4.153	5.858
Real estate related variables						
Vacancy	1204	%	10.581	4.218	2.310	25.474
Stock Δ	1176	sqm	347,905	454,964	-1,199,068	3,797,188
Prime Rent Growth	1204	%	0.926	7.725	-54.930	48.072
1. Target Variable						
RNMY	1204	%	0.000	24.793	-44.784	134.013
2. Target Variable						
RNMRP 10y	1204	%	0.000	8.985	-29.913	19.943
RNMRP 5y	1204	%	0.000	8.956	-29.858	19.999

Note: Δ indicates the first differences of the variable. Sqm stands for square meters.

Source: Own presentation.

From the descriptive statistics table, the need for a natural logarithm transformation of cross-border transaction volume and the stock is apparent, because variables vary substantially with regard to their absolute values. Since the origin of the investment volumes is not available, we are unable to control for exchange rate stability. Yet, we incorporate all monetary values in Euros (€) to form a uniform currency base. Additionally, a correlation matrix provides insights into the common movement of the covariates (see Table 9):[14]

[14] Correlations between timely lagged covariates are not reported. However, the indication of the contemporary realizations sufficiently reveals the potential of crucial correlations.

Table 9: Correlation matrix for cross-border transaction volume model variables

		1	2	3	4	5	6	7	8	9	10	11
1	Cross-border transaction volume	1.000										
2	GDP growth	0.057	1.000									
3	CPI growth Δ	0.005	0.037	1.000								
4	Unemployment rate Δ	-0.014	-0.063	0.023	1.000							
5	Global competitive index	0.122	0.045	0.014	0.021	1.000						
6	Vacancy	-0.165	0.048	0.001	0.003	-0.451	1.000					
7	Stock Δ	0.095	-0.116	0.000	0.003	-0.269	0.104	1.000				
8	Prime rent growth	0.033	0.076	-0.018	-0.014	0.156	-0.197	-0.215	1.000			
9	RNMY	-0.233	-0.003	-0.013	-0.005	-0.621	0.552	0.279	-0.183	1.000		
10	RNMRP 10y	-0.103	0.080	-0.005	-0.011	0.242	0.063	-0.119	0.027	0.244	1.000	
11	RNMRP 5y	-0.102	0.080	-0.006	-0.011	0.244	0.060	-0.131	0.031	0.234	0.999	1.000

Note: Δ indicates the first differences of the variable.

Source: Own presentation.

In line with previous research, we define absolute values greater than 0.25 define as threshold for any econometric issues. The target variable RNMY shows critical correlations with the Global Competitive Index, vacancy and stock. Among the controls, Global Competitive Index yields correlations with stock and vacancy below -0.25. Stock and vacancy show a correlation above 0.25. Even though we estimate a base model with all correlated variables, we try to control for multicollinearity by comparing the results of the specified model with the results of model variations. These variations individually exclude one of the correlated variables.

Lastly, since panel data models may be subject to potential non-stationarity, we carried out panel unit root test to check for econometric distractions (see appendix). For those covariates which suffer from non-stationarity, we used a differencing procedure, in order to generate a stationary time series. After a first differencing, we observe stationary covariates, denoted Δ(x).

To assess the outlined hypotheses, two different methodologies are applied: Pooled OLS, as well as a GAMM. Firstly, an OLS model estimates the linear predictors to evaluate the first hypothesis. The model specification yields the following equation 13:

$$ln(v_{i,t}) = \beta m_{i,t-k} + \beta r_{i,t-k} + \beta relative\ attractiveness_{i,t-k} + \beta time_t + \beta city_i + \varepsilon_{i,t} \quad (13)$$

Here, the natural logarithm of the cross-border transaction volume $ln(v_{i,t})$ observed in a market i in quarter t is a function of the abovementioned domestic macroeconomic variables captured in the vector $m_{i,t-k}$, real-estate-related variables in the vector $r_{i,t-k}$ and one of the measurements for relative attractiveness, captured in vector $relative\ attractiveness_{i,t-k}$.

$$v_{i,t} = Cross - border\ transaction\ volume \tag{14}$$

$$m_{i,t-k} = \begin{cases} GDP\ gr\ \ wth \\ \Delta(CPI\ growth) \\ \Delta(Unemployment\ rate) \\ Global\ Competitive\ Index \end{cases} \tag{15}$$

$$r_{i,t-k} = \begin{cases} Vacancy \\ ln\ (\Delta(Stock)) \\ Prime\ rent\ growth \end{cases} \tag{16}$$

$$relative\ attractiveness_{i,t-k} = \begin{cases} RNMY \\ RNMRP\ 10y \\ RNMRP\ 5y \end{cases} \tag{17}$$

To control for temporal heterogeneity, we use dummy variables labeled as $time$ for each period of the sample. The base period is Q1/2008. City heterogeneity is captured in specification 13 by including $city$ dummies, with Frankfurt representing the reference, considering its approximate geographic European centrality within the sample. $\varepsilon_{i,t}$ represents the error which is not captured in the model.

Since real estate markets are prone to timely delayed effects, we estimate lagged terms up to four quarters for each included covariate (k = 4). Some authors have addressed the influence of transaction activity on cap rates (see e.g. McAllister & Nanda (2016a) and Oikarinen & Falkenbach (2017) who ran their econometric analysis as differently to our procedure). Accordingly, we check our data sample by first carrying out a Granger causality test to evaluate a potentially inverse relationship between the dependent and the target variables.

Even though the abovementioned pooled OLS estimation procedure is capable of testing the first economic hypothesis by isolating a linear c.p. effect on average across the data set of the relative attractiveness, the second hypothesis requires a different approach. To further explore potential nonlinearity we use a second and semiparametric model. The GAMM allows nonlinear as well as linear relationships of the covariates (see equation 18):

$$\ln\left(v_{i,t}\right) = \beta m_{i,t-k} + \beta r_{i,t-k} + f_i\left(relative\ attractiveness_{i,t-k}\right) + \beta time_t + \beta city_i + \varepsilon_{i,t} \tag{18}$$

Here, the function f_i denotes the smoothing function for the relative attractiveness proxy, which is used to check for potential nonlinearity. Thus, we do not estimate a linear predictor for the variables of interest, in contrast to the OLS model. Since the potential nonlinear behavior of the macroeconomic and real-estate-related controls is of minor interest, we introduce a smoothing function only for the target variables. The number of knots is set equal to 20.

3.4 Empirical results

Due to potential inverse relationships between yields and capital flows, we firstly conduct a Granger causality test to detect potential simultaneity bias in our sample (see Table 10):

Table 10: Granger causality test (RNMRP & RNMY – cross-border transaction volume)

Inverse relationship

Dependent	Independent	F statistic	p-value	
RNMRP 10y	ln(Cross-border transaction volume)	0.6708	0.6123	
RNMRP 5y	ln(Cross-border transaction volume)	0.6542	0.6240	
RNMY	ln(Cross-border transaction volume)	2.1227	0.0753	*

Source: Own calculation.

As displayed above, we find strong empirical proof against a potential inverse relationship between cross-border volumes and both RNMRPs. Only for the RNMY is the relationship inversely statistically significant and may therefore cause simultaneity. The standard methodical procedure for accounting for simultaneity is to use an instrument variable approach such as two stage least squares. However, since target variables are of particular interest – unlike controls – we do not search for instruments, but emphasize the potential presence of simultaneity bias with regard to the RNMY.

To test the first hypothesis, we run pooled OLS estimations. The results can be found in Table 11. For each of the three target variables, we estimate the same four specifications. The base model includes all control variables, whereas the second, third and fourth models individually exclude the variables Global Competitive Index (GCI), vacancy and stock, to check for robustness. The selected variables were systematically exchanged, due to the findings within the correlation matrix and to account for potential multicollinearity.

Table 11: Pooled OLS estimation results (cross-border transaction volume)

	Dependent variable: ln (cross-border transaction volume)											
Model	Model 1	Model 1.1	Model 1.2	Model 1.3	Model 2	Model 2.1	Model 2.2	Model 2.3	Model 3	Model 3.1	Model 3.2	Model 3.3
Controls:												
Macroeconomic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Real estate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded control	None	GCI	Vacancy	Stock	None	GCI	Vacancy	Stock	None	GCI	Vacancy	Stock
Target variables:												
RNMY	-0.094	-0.091	-0.086	-0.102								
	(0.082)	(0.082)	(0.087)	(0.083)								
RNMY (-1)	0.086	0.083	0.048	0.099								
	(0.110)	(0.110)	(0.117)	(0.111)								
RNMY (-2)	0.088	0.086	0.111	0.083								
	(0.102)	(0.102)	(0.107)	(0.103)								
RNMY (-3)	-0.163	-0.158	-0.175	-0.180								
	(0.113)	(0.113)	(0.114)	(0.113)								
RNMY (-4)	0.087	0.083	0.093	0.108								
	(0.075)	(0.075)	(0.072)	(0.076)								
RNMRP 10y					0.164	0.158	0.203 *	0.183				
					(0.113)	(0.112)	(0.111)	(0.111)				
RNMRP 10y (-1)					-0.222	-0.230	-0.229	-0.217				
					(0.157)	(0.155)	(0.159)	(0.159)				
RNMRP 10y (-2)					0.335 **	0.339 **	0.306 **	0.333 **				
					(0.155)	(0.152)	(0.155)	(0.155)				
RNMRP 10y (-3)					-0.265	-0.257	-0.247	-0.260				
					(0.173)	(0.169)	(0.173)	(0.174)				
RNMRP 10y (-4)					0.108	0.086	0.116	0.093				
					(0.140)	(0.136)	(0.139)	(0.142)				
RNMRP 5y									0.111	0.106	0.141	0.129
									(0.117)	(0.117)	(0.117)	(0.116)
RNMRP 5y (-1)									-0.149	-0.161	-0.149	-0.141
									(0.159)	(0.158)	(0.162)	(0.161)
RNMRP 5y (-2)									0.311 **	0.320 **	0.282 *	0.307 **
									(0.154)	(0.152)	(0.155)	(0.154)

RNMRP 5y (-3)									-0.259	-0.252	-0.241	-0.254
									(0.173)	(0.169)	(0.174)	(0.174)
RNMRP 5y (-4)									0.102	0.081	0.110	0.088
									(0.140)	(0.137)	(0.139)	(0.143)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	10.141	18.708 ***	-0.386	5.780	3.670	17.658 ***	-8.171	-0.999	4.206	17.750 ***	-7.742	-0.636
	(14.429)	(1.779)	(14.277)	(14.527)	(14.854)	(1.964)	(14.522)	(14.856)	(15.012)	(1.959)	(14.685)	(15.008)
Observations	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064	1064
R^2	0.450	0.450	0.438	0.445	0.452	0.451	0.440	0.447	0.451	0.451	0.439	0.446
Adjusted R^2	0.408	0.410	0.397	0.405	0.410	0.412	0.399	0.407	0.409	0.411	0.399	0.407

Notes: The estimations are based on pooled OLS panel regressions with year and city dummies. "(-t)" denotes the t-th lag of the covariate. The estimation results of the control variables are available upon request. Dummies are included but not reported. Heteroscedasticity and autocorrelation-robust standard errors were used. ***, ** and * represent statistical significance at 0.01, 0.05 and 0.10 levels, respectively. Standard errors are displayed in parentheses.

Source: Own presentation.

Firstly, the explanatory power of the models is in line with related research, ranging around an adjusted R^2 of 0.35 – 0.40. However, when we exclude binaries for the city individuals, we observe estimations (not reported) with declining adjusted R^2 values around 0.10, showing city-specific heterogeneity. Both specified findings are in line with related literature e.g. Devaney et al. (2019). The temporal binaries are predominantly statistically insignificant, indicating temporal homogeneity.

Focusing on the linear predictors of interest, we find on average a positive and statistically significant, c.p. relationship for the RNMRP 10y and 5y within the base models 2 and 3 for the second lag. The model variations 2.1 – 2.3 and 3.1 – 3.3 provide similar results, emphasizing the robustness of the results. One can derive two insights from these findings. First, cross-border investors favor higher risk premia when looking for investment opportunities in Europe. Interestingly, this also applies to investors who anticipate long- and medium-term holding-periods. The models report a c.p. effect on average around 0.3% per base point relative risk premium (since betas range around 0.3).

Second, if a city offers a relative risk premium above the European mean, it generally takes six months until cross-border capital flows into the respective market. The specified finding is in line with expectations due to search and transaction phases in direct markets. Crosby & McAllister (2004) and Bond et al. (2007) state an average transaction period in UK commercial real estate markets of approximately six to nine months. Model 2.2 also shows a statistically significant positive sign for RNMRP 10y for the contemporary covariate (lag = 0), which however is not investigated any further.

Considering the target variable RNMY, no statistically significant relationship between relative yield and inflowing transaction volume could be revealed. This finding adds to the study of Devaney et al. (2019), who find an insignificant relationship between cap rates and general transaction activity in commercial real estate markets. Concluding the OLS result section, the first hypothesis can be confirmed after differentiating between yields and risk premia. Thus, relative attractiveness contributes to the existing absolute measures of determinants of cross-border transactions. However, relative attractiveness of cross-border investors is only perceived in terms of relative risk premia and not relative yields.

In addition to the fully parametric model, we assess hypothesis two by specifying semi-parametric GAMMs. We use smoothing functions for the RNMRP only, since the RNMY has not shown significance in the fully parametric approach (models 1 – 1.3). The GAMM specifications are identical to the linear ones and denoted with a "G", to ensure easy comparability with the OLS peer. All other covariates are still included with a linear predictor. However, we do not report the coefficients of still parametrized lags of the RNMRP, since they are already reported above (see Table 11). Instead,

Table 12 presents the estimated degrees of freedom and the statistical significance for the smoothing functions of the covariates as an expression of nonlinear behavior.

Table 12: GAMM estimation results for penalized spline functions of non-parametric covariates

	Dependent variable: ln (cross-border transaction volume)							
Model	Model G.2	Model G.2.1	Model G.2.2	Model G.2.3	Model G.3	Model G.3.1	Model G.3.2	Model G.3.3
Controls:								
Macroeconomic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Real estate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded control	None	GCI	Vacancy	Stock	None	GCI	Vacancy	Stock
Target variables:								
RNMRP 10y	-	-	7.272 ***	-				
			(2.887)					
RNMRP 10y (-1)	-	-	-	-				
RNMRP 10y (-2)	6.92 ***	6.999 ***	2.089 *	6.853 **				
	(2.721)	(2.753)	(2.397)	(2.605)				
RNMRP 10y (-3)	-	-	-	-				
RNMRP 10y (-4)	-	-	-	-				
RNMRP 5y					-	-	-	-
RNMRP 5y (-1)					-	-	-	-
RNMRP 5y (-2)					6.905 ***	6.983 ***	7.427 ***	6.843 **
					(2.636)	(2.664)	(3.238)	(2.520)
RNMRP 5y (-3)					-	-	-	-
RNMRP 5y (-4)					-	-	-	-
Time dummies	YES	YES	YES	YES	YES	YES	YES	YES
City dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1064	1064	1064	1064	1064	1064	1064	1064
Adjusted R^2	0.421	0.423	0.416	0.418	0.420	0.423	0.414	0.407

Notes: The estimations are based on GAMM regression, using penalized splines and the Gaussian link family. "(-t)" behind the name of the covariate denotes the t-th lag. The estimated degrees of freedom of the smooth terms are reported. The joint significance of the smoothing terms expressed by the F-test values is displayed in parentheses. The remaining parametrized covariates are not reported, but are identical to the specifications displayed in Table 116. Heteroscedasticity and autocorrelation-robust standard errors were used. ***, ** and * represent statistical significance at 0.01, 0.05 and 0.10 levels, respectively.

Source: Own presentation.

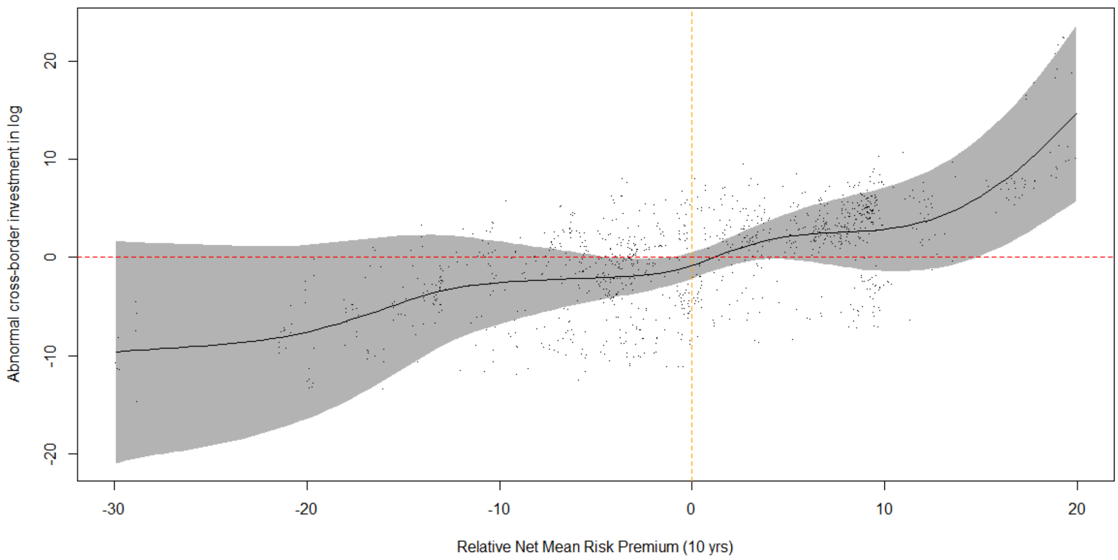
Firstly, the results reveal slight differences for the adjusted R^2. Since we only use smoothing functions for a single or two covariates per specification, a few models (e.g. models G.2, G.2.2, G.3, and G.3.2) show increased explanatory power by about one percentage point.

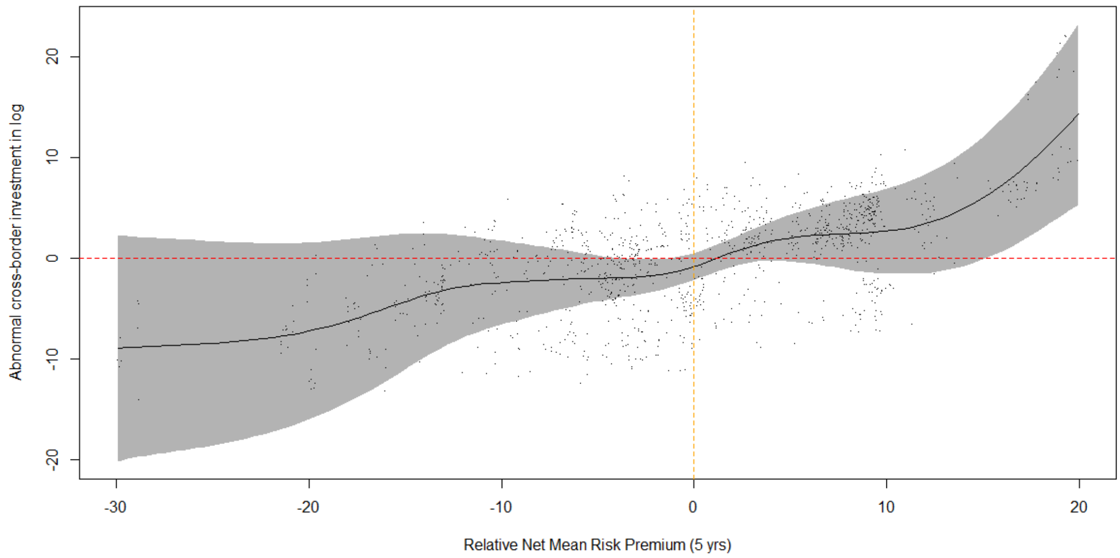
More importantly, the specified smooth terms unanimously show statistical joint significance, as expressed by the F-test values for each smooth term. The individual nonlinear behavior for each of the target variables can be assessed by the estimated degrees of freedom of the respective smooth term. The interpretation works as follows: Estimated degrees of freedom equal to one represent an entirely linear relationship between the dependent and independent variables across the entire distribution. Hence, the larger the difference of the estimated degrees of freedom from one, the stronger the nonlinearity within the relationship becomes.

Here, most smoothing functions show estimated degrees of freedom around 7. Only the second lag of the RNMRP 10y in model G.2.2 shows a much smaller value. Nonetheless, the function is still statistically significant. Thus, we can confirm the nonlinear behavior of the target variables across all specifications.

Since smoothing functions of GAMMs do not report a single estimate, a numerical interpretation is not possible. Instead, we report the graphical illustration of selected and representative functions and the respective partial residuals, as displayed below (see Figure 3). The functions were chosen from the base models G.2 and G.3. Other models show similar results.

Figure 3: Penalized spline functions of RNMPR 10y and RNMRP 5y – models G.2 & G.3





Source: Own presentation.

The graphic display shows the smoothing function across the distribution of the RNMRPs on the x-axis. The y-axis represents the divergence of the smoothing function from the mean of the dependent variable. Accordingly, we can derive various findings from the graphic inspection of the functions. Firstly, we can confirm the linear models and their predictions of a constantly increasing trend across the entire bivariate distribution. Secondly, the almost perfect match of the smooth term and the vertical and horizontal line indicate market efficiency, because a relative premium of zero matches a smooth term value of zero. The horizontal line also shows a negative effect of the risk premia on the mean cross-border transaction volume below zero.

However, most interestingly we observe a convex shape of the smoothing terms for values in the right tail of the bivariate distribution. This indicates that markets with extreme risk premia also attract extremely high capital inflows, since especially the upper tail of the distribution has a convex shape. The same applies inversely to the lower tail, causing transaction volumes to decline heavily below the mean. The results are similar for the RNMRP 5y.

Lastly, the combination of the two approaches can be summarized in terms of the following empirical results: We find both, statistical significance for the linear predictor as well as the corresponding smoothing terms of risk premia. Thus, the combination of the empirical findings reveals a linear c.p. effect and also nonlinear behavior in the tails of the bivariate distributions of dependent and independent covariates.

3.5 Conclusion and further aspects

This study presents a new approach to explaining commercial cross-border transaction activity, namely the development of a city's relative attractiveness in comparison to its peers. We find an on average, c.p. and statistically significant relationship between relative risk premia and inflowing cross-border capital into office properties in Europe. We thus confirm the existence of a risk-premium-chasing behavior of cross-border investors with regard to relative city attractiveness. Moreover, we find empirical evidence for a timely lagged effect, since statistical significance can be observed predominantly for the two-quarter-delayed covariates.

However, a decisive differentiation for the economic finding is needed. The measurement of relative yields is unanimously statistically insignificant, underlining the importance of risk premia instead of pure yields as explanatory variable for cross-border inflows. Nonetheless, we conclude and also extend the existing body of literature by showing the relationship between the investor calculus of relative attractiveness and capital flows as a new determinant. Thus, we can partly justify our first hypothesis, while highlighting the importance of differentiating between relative yields and risk premia.

Moreover, we find evidence for a potential nonlinear behavior of the relative attractiveness measures, expressed by the statistical significance of the smoothing terms in the GAMM. Consequently, we see evidence in favor of the second hypothesis. Interestingly, we find a curvy or convex shape of the smoothing functions, especially in the tails. This finding indicates extreme capital inflow behavior for locations which also offer extreme relative premia. Thus, we conclude, that especially risk-friendly cross-border investors trigger abnormally high investment flows into real estate markets.

Some limitations apply to the used data. Firstly, we analyze European data only. The same analysis on a larger scale appears promising, as proposed on a global level by Devaney et al. (2019). Secondly, the depth of the data can be discussed. As outlined by Lieser & Groh (2014), a large variety of covariates show a statistically significant relationship with foreign investment volumes. However, since we control for the most important types of impact variables, the explanatory power of the models are in line with previous studies. Thus, we perceive the selected controls as a sufficient set of variables. Econometric robustness tests also confirm the stability of the results across various specifications.

Practical implications can be derived from an investment management and risk controlling perspective. The understanding of determinants in market transaction volumes is an important factor for anticipating inflowing capital and potential capital value changes. Therefore, for example positive divergence from the benchmark is expected to cause on average higher inflows of cross-border capital. Equity investors can use the insights especially for their disinvestment strategies. In this context, they can specifically address foreign buyers, when risk premia in markets of their existing property investments move above the European mean, since cross-border investors are expected to invest in these locations. Financing debt investors on the other hand can expect sales of standing investments to cross-border investors in advance of their expected maturity, if risk premia of the market move above the European mean. Secondly, financing institutions can benefit from cross-border investors by offering funds to them and consequently expect new business opportunities. Early anticipation of potential financing requests will help to plan refinancing and money allocation activities.

Further useful research may be undertaken by differentiating between the geographic origin and type of investor. Considering return chase behavior, Devaney et al. (2018) noted that different nationalities may matter. Moreover, focusing on other property types would reveal whether the relative attractiveness is generally applicable to other markets and not a phenomenon unique to the commercial- and office sector. Lastly, extending the present approach of relative attractiveness not only to the yield and risk premium side of a market, but to other covariates, may provide further insights.

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3.7 Appendix

Table 13: Levin-Lin-Chu stationarity test for cross-border transaction volume model variables

Variable	Test statistic	P-Value	Variable with Δ	Test statistic	P-Value
Dependent Variable					
Cross-border transaction volume	-4.036	0.000			
Macroeconomic variables					
GDP growth	-11.571	0.000			
CPI growth	0.904	0.900	CPI growth Δ	-21.245	0.000
Unemployment rate	14.910	1.000	Unemployment rate Δ	-7.503	0.000
Global Competitive Index	-3.552	0.000			
Real estate related variables					
Vacancy	-8.816	0.000			
Stock	1.276	0.899	Stock Δ	-5.293	0.000
Prime Rent Growth	-1.958	0.030			
1. Target Variable					
RNMY	-1.226	0.110			
2. Target Variable					
RNMRP 10y	-1.355	0.090			
RNMRP 5y	-1.694	0.050			

Note: Δ indicates the first differences of the variable. The maximum lag was set to 4, since our maximum time lag within the econometric model is equal to 4.

Source: Own presentation.

4 Volatility Targeting for US Equity REITs – A strategy for Minimizing Extreme Downside Risk?

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Journal of Real Estate Portfolio Management (accepted for publication)

Abstract

The study examines the feasibility of the so-called Volatility Targeting investment style to minimize extreme downside risk for US Equity REITs. The empirical study applies a two-stage approach: First, a back test of buy and hold, and VT based on various volatility estimators for each equity REIT security between 01/01/1999 and 01/01/2019 is performed. Subsequently, a mean-$CVaR_{\alpha}$-optimization for the entire data set as well as the different equity REIT subclasses is carried out. The study finds $CVaR_{\alpha}$ reductions of the Volatility Targeting strategy in comparison to buy and hold across the majority of subclasses, as well as the entire sample. Interestingly, these improvements differ across the REIT subclasses and volatility estimators.

4.1 Introduction

The risk management of securitized equity positions such as equity REITs is a central field of interest for institutional investors as well as for academia. Classic tools to protect positions from extreme losses are derivative overlay strategies including put options (Hocquard et al., 2013), stop-loss-strategies, constant portfolio insurance or market-signal approaches based on macro data like the OECD leading indicator (Hocquard et al., 2015).

Nonetheless, these management tools can entail OTC costs and counterparty risk. Accordingly, the scientific discussion has shifted towards alternative techniques. In this context, the debate has focused on using the volatility of a position in order to manage its risk through active asset allocation. The described logic is the foundation of the newly developed approach of the so-called *Volatility Targeting* (VT).

VT describes the active allocation management based on a volatility measure, to target a predefined level of volatility, or risk respectively. Thus, VT adjusts the allocation dynamically and hence the risk exposure, in order to stabilize the realized volatility across time and thus minimize the probability of extreme losses (Fleming et al., 2001). Since extreme losses are more likely in periods of increased market volatility, the idea of managing the extreme downturn risk of equity REITs through allocation management based on a volatility measurement does indeed appear promising.

Accordingly, and as essential prerequisites, the financial literature names two decisive characteristics of financial time series of equity positions for VT, aimed at enhancing performance and protecting from heavy downturn risk. These are the *leverage effect* as well as *volatility clustering* (Harvey et al., 2018). For equity REITs, empirical studies have repeatedly shown the existence of the features referred to above (e.g. Cotter & Stevenson, 2007). However, there has so far been no comprehensive, empirical study on the risk management potential of VT in equity REIT markets. The issue thus constitutes a gap in the literature. Interestingly, equity REITs can be of particular interest for volatility-based risk management using the leverage effect since their business models are levered higher than manufacturing or industrial companies due to the legal regulations for these vehicles (Chung et al., 2016).

Thus, the central research question of the present study can be summarized as follows: Does VT offer economically efficient downside risk protection for investors of securitized real estate positions, namely equity REITs? Accordingly, the methodologically interesting question arises as to what volatility *estimator* provides the most efficient tail risk protection for investors. In this context, the literature cites the historical volatility of the individual security on the one hand, or implied volatility of the broad stock market and GARCH modelling as potential volatility estimators on the other hand (Cirelli et al., 2017).

In order to provide insight into these issues, the article is structured as follows: Section 2 reviews the literature on VT and the necessary equity REIT volatility characteristics. Subsequently, the section derives the hypotheses for the empirical study. Section 3 describes the daily US equity REIT return data for the study. In Section 4, the empirical methodology is explained, followed by Section 5 in which the results are presented. Section 6 concludes and outlines potential further research on VT in REIT markets.

4.2 Literature review and hypothesis derivation

The relevant bodies of literature for deriving the hypotheses for the own empirical approach can be divided into the following two areas: Conceptual and empirical articles on VT, as well as volatility characteristics of equity REIT returns. Conceptual literature on VT was first introduced by Fleming et al. (2001). The basic idea is the adjustment of position inversely towards a volatility measurement, since expected returns are a negative function in volatility. This mechanism is known in financial literature as the leverage effect (Chorro et al., 2018), and the effect is highly relevant to REITs due to two characteristics: Firstly, REITs have higher leverage ratios than industrial companies. Secondly, REITs pay the vast majority of their earnings as dividends to their investors, and are heavily exposed to liquidity risk (Chung et al., 2016).

The empirical literature on VT has so far covered various asset classes. Methodologically speaking, a large portion of the literature has focused on using back testing procedures to test potential improvements of VT in comparison to buy and hold strategies (Cooper, 2010; Hocquard et al., 2013; Perchet et al., 2014; Cirelli et al., 2017). Regarding the target variable, the literature has analyzed both, the return (e.g. Cooper, 2010; Perchet et al., 2014) as well as explicitly the (downside) risk side of positions (Hocquard et al., 2013). The analyzed asset classes contain mainly classic public equities (Fleming et al., 2001; Cooper, 2010; Hallerbach, 2012; Hocquard et al., 2013), currencies, bonds as well as commodities (Harvey et al., 2018).

Fleming et al. (2001) represents the starting point within the literature, using a dynamic portfolio optimization approach. Their study analyzes equity positions from 03/01/1983 through 31/12/1997. Their volatility-timed portfolios outperform the ex ante optimal static strategies, measured by the Sharpe Ratio. Cooper (2010) has demonstrated the benefit of VT for global equity indices. For a back test performed between 1950 and 2009, the author presents improvements in ex post annual returns as well as volatility and maximum drawdown, when using VT based on historical volatility. For European indexed equities, namely EURO STOXX, Hallerbach (2012) empirically proves the superior performance of VT between 01/01/2003 and 31/12/2011. Thus, the resilience of VT to geographic regions and their differences of equities can be assumed.

Hocquard et al. (2013) do not use single index data, but form a globally weighted equity portfolio between 1990 and 2011. Again, the VT strategy outperforms a base equity portfolio. The research highlight is a positive skew of the portfolio, in comparison to the – traditionally – negative skew of the base case (-0.71 vs. 0.21). Albeverio et al. (2013) add the detail that performance improvements to VT are resilient to interest rate changes, based on a back test for the S&P500 between 1963 and 2008 in various debt cost regimes. As mentioned above, since REITs are classically highly levered, this finding is particularly interesting for the asset class of interest, because REITs may be sensitive to debt cost changes.

Perchet et al. (2014) analyze data of the S&P500 between 01/01/1990 and 31/05/2013, using a back test for buy and hold vs. VT. The study confirms improvements in excess return, Sharpe Ratio as well as maximum and average drawdown. The decisive methodical value added by the study is the introduction of GARCH volatility modelling based on one-day-ahead forecasts as the volatility estimator.

Based on the approach of Perchet et al. (2014), a controversial methodology detail within the scientific discussion has gained attention, namely the appropriate measurement of volatility. In this context, Cirelli et al. (2017) compare VT based on historical volatility with implied volatility. For their S&P500 data set from 1990 – 2015, they show higher downside risk protection by implied volatility based on the CBOE Volatility Index (VIX). This finding is in line with older studies on the informational power of option markets on expected returns of equities such as Cao et al. (2005), Pan & Poteshman (2006) and Whaley (2009). Dreyer & Hubrich (2017) noted the decisive detail of testing other volatility estimators than the historical volatility. They point out, that "*a meaningful share of the return distribution is explained by extrapolation of recently experienced volatility*". This remark shows the crucial challenge of VT based on historical volatility: A large portion of return variation is explained by historical volatility, but explicitly not the entire variability. Thus, a remaining, and from the investor point of view uncertain portion of variability, remains unexplained and potentially dangerous.

For the VIX, an application to REITs appears complicated, since it measures the implied volatility of options of the S&P500 constituents. For this methodological challenge, the study of Anuruo & Murthy (2017) provides a legitimation, since the authors show a statistically significant relationship between the VIX and returns of US equity REIT positions. Alternatively, Chung et al. (2016) construct REIT-specific, non-aggregated implied volatility by using the Ivy DB OptionMetrics.

As mentioned above, the second relevant body of literature covers empirical studies on the necessary volatility clustering and the leverage effect for equity REIT returns. The clustering effect denotes the fact, that the volatility of stock returns tends to cluster, meaning that periods of high volatility are followed by high volatility and vice versa. Methodologically, literature has largely focused on GARCH models. Cotter & Stevenson (2007) is the first article to analyze volatility clustering across time. Their GARCH approach to equity REIT returns from 1993 to 2005 empirically reveals a strong clustering effect. Especially interesting are findings regarding the size of REITs, namely that the volatility of largely capitalized vehicles is more prone to the *overall* market volatility. Bredin et al. (2007) find evidence supporting responses of US equity REITs' volatility to changes in monetary policy. Thus, shifts in the volatility of equity REITs can be subject to unanticipated changes in debt costs. Similar results were provided by Huerta et al. (2016), who show a statistically significant negative impact of diminishing market liquidity between Q4/2008 – Q2/2009 on the volatility of equity REITs. Jirasakuldech et al. (2009) find a time-varying, but persistent and predictable conditional volatility of US equity REITs from 1972 – 2006 using monthly data within a GARCH approach. Case et al. (2013) apply a Markov-Switching model to US REIT returns from 1972 – 2008, and find two clearly divided volatility regimes. In sum, the majority of the literature states that REIT returns are subject to volatility clustering.

On the other hand, the leverage effect for equity REITs was analyzed by Li (2016). Using 1972 – 2013 US data, the author applies a factor model including the volatility of the individual security. The results indicate a statistically significant negative relationship between volatility and future returns. Recently, the leverage effect of US equity REITs was also analyzed by Kawaguchi et al. (2017). Their January 1985 to October 2012 data sample reveals a time-variant strength of the leverage effect. The authors use subsets of the "Greenspan era" between 1994 and 2006 in comparison to both, the pre and post time frame of the era. The authors cite the study of Christie (1982) as explanatory article, highlighting interest rates as the central economic reason for regime shifts in equity volatility. Additionally, Yang et al. (2012) provide empirical evidence of asymmetric volatilities of equity REITs, since their business models are highly levered and thus over-proportionally exposed to increases in market volatility, as mentioned above. Similar results are provided by Chung et al. (2016). Hence, the existence of the leverage effect appears to be feasible for equity REITs. Taking the above-outlined literature into consideration, the following hypotheses can be derived as the foundation for the own empirical study:

Hypothesis 1: *VT-based risk management of equity REIT positons improves the downside risk-return-profiles in comparison to buy and hold* (e.g. in line Perchet et al., 2014, Hocquard et al., 2013).

Other asset classes, especially equities have shown the performance improvements of VT. The same hypothesis is stated for equity REIT positions, since they show the necessary volatility clustering (e.g. Cotter & Stevenson, 2007) and the leverage effect (e.g. Kawaguchi et al., 2017).

Hypothesis 2: *Volatility estimation based on implied volatility using the VIX Index and GARCH-based VT strategies improve the downside risk protection of REIT positions in comparison to historical volatility measurements* (e.g. in line with Cirelli et al., 2017)**.**

Implied volatility modelling has a higher explanatory power for future market behavior. Thus, implied volatility, measured by the VIX on the S&P 500 reduces the downside risk for equity REIT positions in comparison to historical volatility. Similar expectations apply to GARCH-based modelling of future volatility, since equity REIT volatility may be predictable (Jirasakuldech et al., 2009).

4.3 Data and descriptive statistics

The study uses daily log US equity REIT close price returns between 01/01/1999 and 01/01/2019, with a total number of 5,031 observations per security, generated from Yahoo Finance. The beginning of the timeframe was chosen for two reasons. Firstly, the analysis is intended to cover the most recent periods of prominent bearish markets ("tech bubble" starting in August 2000 as well as the financial crisis starting in 2008), in order to stress how the strategy of interest deals with heavy downturns. Secondly, the methodological homogeneity with important reference studies such as Hocquard et al. (2013) are of interest, to ensure comparability with the existing body of literature in other asset classes.

The securities were selected from the NAREIT database. In order to establish a stable data sample over the entire horizon, the security has to be constituent of the index for the entire sample span from 01/01/1999 to 01/01/2019. The described selection pattern leads to 54 US equity REITs being part of the data sample, with a complete sample size of 271,674 return observations.

Within the sample, eight subclasses were identified, according to the classification of the NAREIT database: office, industrial, retail, residential, diversified, lodging and resorts, self-storage and health care. For the sample of equity REITs, the following descriptive statistics could be obtained:

Table 14: Descriptive statistics of daily US equity REIT returns (01/01/1999 – 01/01/2019)

Security (ticker)	mean	Std. dev.	median	min	max	range	skew	kurtosis
				Office				
ARE	0.001	0.019	0.001	- 0.241	0.181	0.422	-0.197	16.622
BDN	0.000	0.023	0.001	-0.242	0.255	0.497	0.416	23.877
BXP	0.001	0.020	0.000	-0.167	0.239	0.406	0.522	19.434
CLI	0.000	0.021	0.000	-0.226	0.237	0.463	0.732	22.504

CUZ	0.000	0.024	0.000	-0.257	0.326	0.583	0.966	26.915
HIW	0.001	0.021	0.000	-0.254	0.233	0.486	0.435	21.058
KRC	0.001	0.020	0.001	-0.247	0.204	0.452	0.254	18.741
OFC	0.001	0.021	0.000	-0.250	0.175	0.425	0.202	14.218
SLG	0.001	0.026	0.001	-0.278	0.408	0.686	0.981	37.503
				Industrial				
DRE	0.001	0.025	0.001	-0.316	0.381	0.697	0.598	39.470
EGP	0.001	0.018	0.001	-0.194	0.159	0.354	-0.037	11.127
FR	0.001	0.030	0.001	-0.319	0.512	0.831	2.127	48.990
PLD	0.001	0.024	0.001	-0.301	0.263	0.564	0.208	29.842
PSB	0.001	0.017	0.000	-0.145	0.179	0.324	0.459	12.623
				Retail				
ADC	0.001	0.022	0.001	-0.291	0.290	0.581	0.727	26.951
AKR	0.001	0.019	0.000	-0.175	0.147	0.322	0.091	8.907
BFS	0.001	0.019	0.000	-0.166	0.149	0.315	0.233	8.417
CBL	0.000	0.031	0.001	-0.360	0.465	0.825	0.462	29.852
FRT	0.001	0.018	0.001	-0.224	0.217	0.441	0.434	21.475
KIM	0.001	0.023	0.001	-0.246	0.337	0.583	1.100	29.044
MAC	0.001	0.025	0.001	-0.268	0.318	0.586	0.551	28.093
NNN	0.001	0.018	0.001	-0.215	0.169	0.384	0.057	15.467
O	0.001	0.018	0.001	-0.198	0.216	0.413	0.921	20.781
PEI	0.000	0.029	0.000	-0.276	0.324	0.599	0.785	22.492
REG	0.001	0.020	0.000	-0.222	0.221	0.442	0.356	19.600
RPT	0.000	0.022	0.000	-0.241	0.324	0.565	0.495	26.862
SKT	0.001	0.018	0.001	-0.149	0.160	0.310	0.270	9.077
SPG	0.001	0.021	0.001	-0.200	0.254	0.454	0.936	21.632
TCO	0.001	0.022	0.000	-0.216	0.235	0.451	0.618	19.197
WRI	0.001	0.021	0.001	-0.220	0.255	0.476	1.160	26.605
				Residential				
AIV	0.001	0.023	0.001	-0.271	0.276	0.547	0.191	23.051
AVB	0.001	0.019	0.001	-0.171	0.181	0.352	0.365	13.717
BRT	0.001	0.024	0.000	- 0.196	0.405	0.602	2.640	48.217
CPT	0.001	0.020	0.001	-0.169	0.224	0.393	0.724	19.287
EQR	0.001	0.021	0.001	-0.216	0.236	0.452	0.834	24.249
ESS	0.001	0.018	0.001	-0.197	0.149	0.346	-0.020	13.359
MAA	0.001	0.019	0.001	-0.228	0.230	0.459	0.538	22.979
SUI	0.001	0.018	0.000	-0.192	0.156	0.348	0.179	13.260
UDR	0.001	0.020	0.001	-0.190	0.175	0.365	0.274	16.198
UMH	0.000	0.016	0.000	-0.117	0.127	0.244	0.327	7.400
				Diversified				
ALX	0.001	0.020	0.000	-0.228	0.249	0.477	0.493	22.274
LXP	0.001	0.027	0.000	-0.342	0.309	0.652	0.537	28.974
OLP	0.001	0.024	0.000	-0.218	0.344	0.561	1.960	36.296
VNO	0.001	0.020	0.000	-0.194	0.222	0.416	0.587	18.883
WRE	0.000	0.019	0.000	-0.200	0.188	0.388	0.268	15.550
				Lodging & Resorts				

HPT	0.001	0.022	0.001	-0.214	0.296	0.510	0.716	26.493
IHT	0.001	0.047	0.000	-0.275	0.436	0.711	1.059	12.173
				Self Storage				
PSA	0.001	0.019	0.001	-0.187	0.203	0.390	0.655	17.132
				Health Care				
HCP	0.001	0.021	0.001	-0.167	0.228	0.394	0.790	17.808
HR	0.001	0.020	0.001	-0.209	0.198	0.407	0.289	15.761
LTC	0.001	0.022	0.000	-0.269	0.162	0.431	-0.123	14.899
NHI	0.001	0.020	0.001	-0.223	0.207	0.431	-0.030	12.290
OHI	0.001	0.027	0.000	-0.341	0.240	0.581	0.094	17.306
UHT	0.001	0.018	0.000	-0.165	0.179	0.345	0.269	9.714

Source: Own presentation.

The descriptive statistics report non-negative mean returns for all US equity REITs over the entire sample duration, indicating positive inflation protection for each vehicle. The standard deviation ranges between 0.01 and 0.03 for most equity REITs. The majority of securities display minimum values of a single daily extreme loss of -0.2 to -0.35. Similar amplitudes apply to the maximum values, which are nonetheless of rather limited relevance to the present study. Regarding the skew of the return distributions, only five REITs in the sample show a negative skew. The values for the kurtosis unanimously reveal positive values, which indicate leptokurtic distributions.

Within the relevant body of literature a potential data cleaning process is subject to discussion. Papageourgiou et al. (2015) stress the need to winsorize extreme returns in order to smooth the return series. Extreme returns, however, are of particular interest for the present study, since they represent the extreme downside risk that is central to this article. A data cleaning of the return series is thus intentionally avoided.

The correlations per subclass (see Chapter 4.8) are almost unanimously positive. In line with expectations, the values are predominantly greater than 0.5, indicating homogenous return co-movements within the subsamples. Significantly lower, but still positive correlations can only be observed for the residential REIT subclass. The only REIT subclass to show a single negative correlation is the lodging and resort REIT class.

4.4 Methodology

In line with previous studies, the present article uses a back testing approach of the following four strategies, to analyze the extreme downside risks associated with each approach:

- Buy and hold (reference),
- VT based on historical volatility,
- VT based on the VIX,

- VT based on one-day-ahead GARCH volatility forecasts.

A value of 12% p.a. was chosen as the target volatility, as proposed by Hocquard et al. (2015). However, regarding the target annual volatility, Papageorgiou et al. (2015) point out that the targeted value cannot be chosen *wrongly*. Instead, the target annual volatility is a sole function of investor risk-appetite. Both Cooper (2010) and Albeverio et al. (2013) also show the resilience of VT efficiency improvements to different levels of targeted annual volatility.

The back test uses the specified three other different volatility estimators for the VT, so as to assess the second hypothesis. The study uses either the historical volatility of the individual security with a 30 day time frame, the implied volatility of the VIX, or a GARCH volatility forecast. The VIX value is taken from the open price of the index on the day of reallocation. The latter estimator is defined by a one-day-ahead forecast, with a standard GARCH(1,1) model, as introduced by Bollerslev (1986). According to the volatility estimator of choice, the allocation or weight respectively w_t towards a particular security will be adjusted by (Perchet et al., 2014):

$$w_t = \frac{\kappa}{\sigma_t}, \qquad 0 < w_t < \infty \tag{19}$$

with target volatility κ, and the annualized estimated volatility σ_t. For example, if the estimator calculates a volatility of 20% p.a., given a target volatility of 12% p.a., the resulting weighting of the security equals $w_t = {}^{0.12}/_{0.2} = 0.6$.[15] The VT-based return, denoted by r_t^{VT}, equals the product of the return r_t of the actual time series multiplied by the weight, w_t:

$$r_t^{VT} = r_t \frac{\kappa}{\sigma_t} = r_t w_t \tag{20}$$

The length between points of potential reallocation is set to 30 days (in line with Hocquard et al., 2013). Several studies have shown the impact of changes to daily, weekly, or monthly rebalancing rhythm (Morrison & Tadrowski, 2013), without significant changes to the results. Interestingly, Marra (2017) proved a rescaling error caused by excessively frequent (weekly) rebalancing. Furthermore, Perchet et al. (2015) show that the gains in the Sharpe Ratio are resilient to rescaling rhythm changes.

After back testing the strategies, the study applies modern portfolio theory in order to analyze whether potential extreme downside risk minimizations are also *economically efficient*. The analysis

[15] If $\kappa > \sigma_t$ applies, the weight w_t can also be >1.

uses the entire sample as well as the specified subclasses according to the NAREIT Index, to check for potential heterogeneity across equity REIT types.[16] Decisively, the optimization will specifically avoid the classic mean-variance-analysis. Instead, a mean- $CVaR_\alpha$-approach is chosen, since the downside risk is of particular interest (Rockafellar & Uryasev, 2000). Within the downside risk metrics, the $CVaR_\alpha$ risk measure was chosen in favor of the classic $CVaR_\alpha$ since the latter does not represent a coherent risk measure according to Artzner et al. (1999).

The study uses the minimization problem of Rockafellar & Uryasev (2000). Consequently, the investor seeks to minimize the downside risk, expressed by the $CVaR_\alpha$ for a given level of expected return, by allocating exposure to the assets within the investment horizon. Alpha is set to 0.95. Additionally, the quantitative analysis also assumes no short-selling and no full investment, since the decision as to whether funds are fully invested or not is already subject to the VT allocation algorithm (see equation 20). The performance assessment of the portfolio optimization is expressed by the stable tail adjusted risk ratio (STARR, as introduced by Biglova et al., 2004):

$$STARR = \frac{\mathrm{E}(r_p - r_f)}{CVaR_\alpha(r_p)} \tag{21}$$

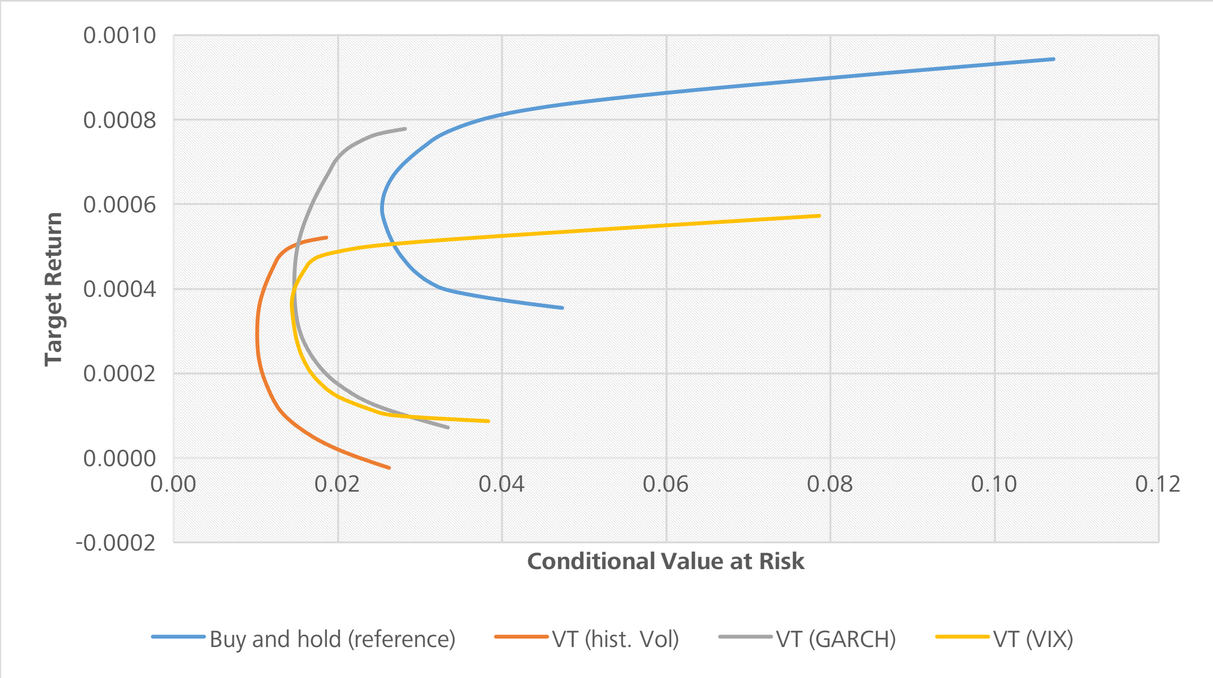
The numerical analysis does not use conventional performance measures such as the Sharpe- or Sortino-ratio of mean-variance optimization, because it focuses on extreme downturn risk, as measured by the STARR. The ratio expresses the excess return in relation to the downside risk, measured by the $CVaR_\alpha$. The risk-free rate is calculated as the average daily return of the 10 year US Treasury bill across the entire sample duration.

4.5 Empirical results

The results are based on the daily log returns for the specified securities, under buy and hold or the three VT-based approaches with differing volatility estimators. The results are presented in a two-way approach: graphically by plotting the efficiency frontiers of the portfolios, as well as numerically by means of the STARR (see equation 21). Firstly, the following figures display the efficiency frontiers of the strategies for the entire sample, and subsequently for the subsamples.

[16] There is no portfolio optimization for the subclass "self storage", since there is only a single security within the class of REITs, and thus no possible portfolio formation. The security is part of the entire investment horizon ("All REITs").

Figure 4: Efficiency frontiers within mean-$\mathbf{CVaR_{0.95}}$-framework (All REITs)

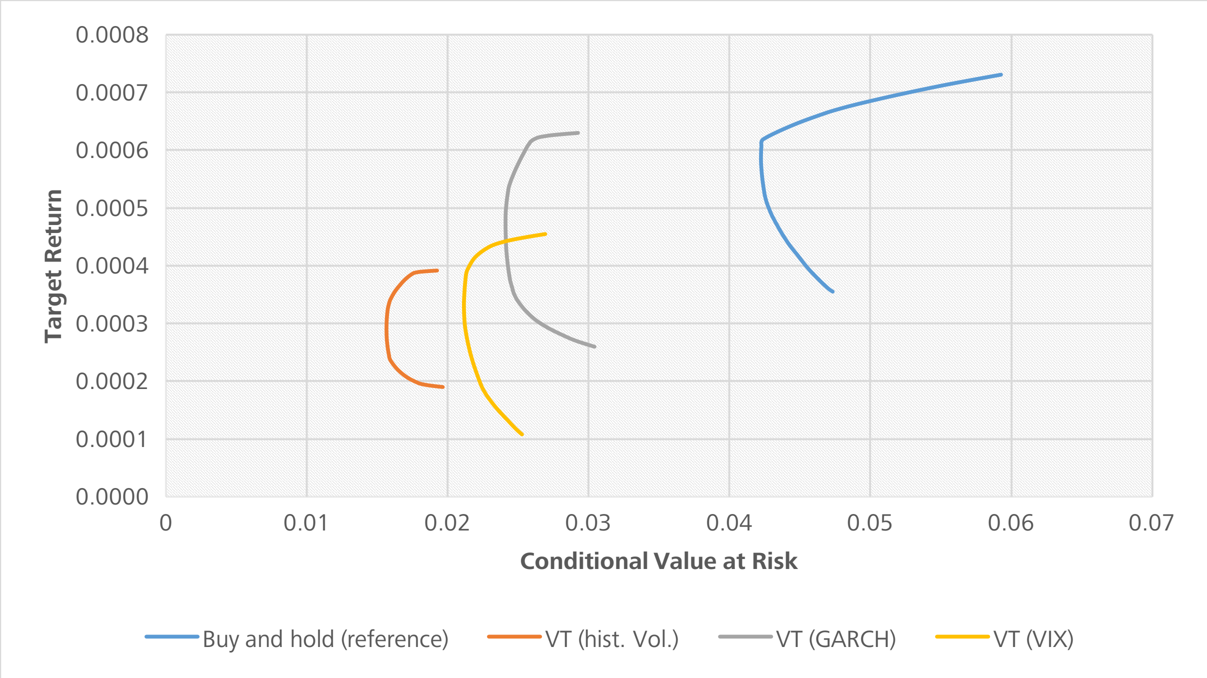


Source: Own presentation.

Figure 4 reveals the mean-$CVaR_{0.95}$-frontiers for the entire sample. Most importantly, all VT-based strategies show downturn risk reduction potential for the entire REIT sample. The graph shows that VT-based strategies are generally downside risk-reducing, since all efficiency frontiers are on the left of the benchmark strategy of buy and hold. The only exception is the VT based on the VIX.

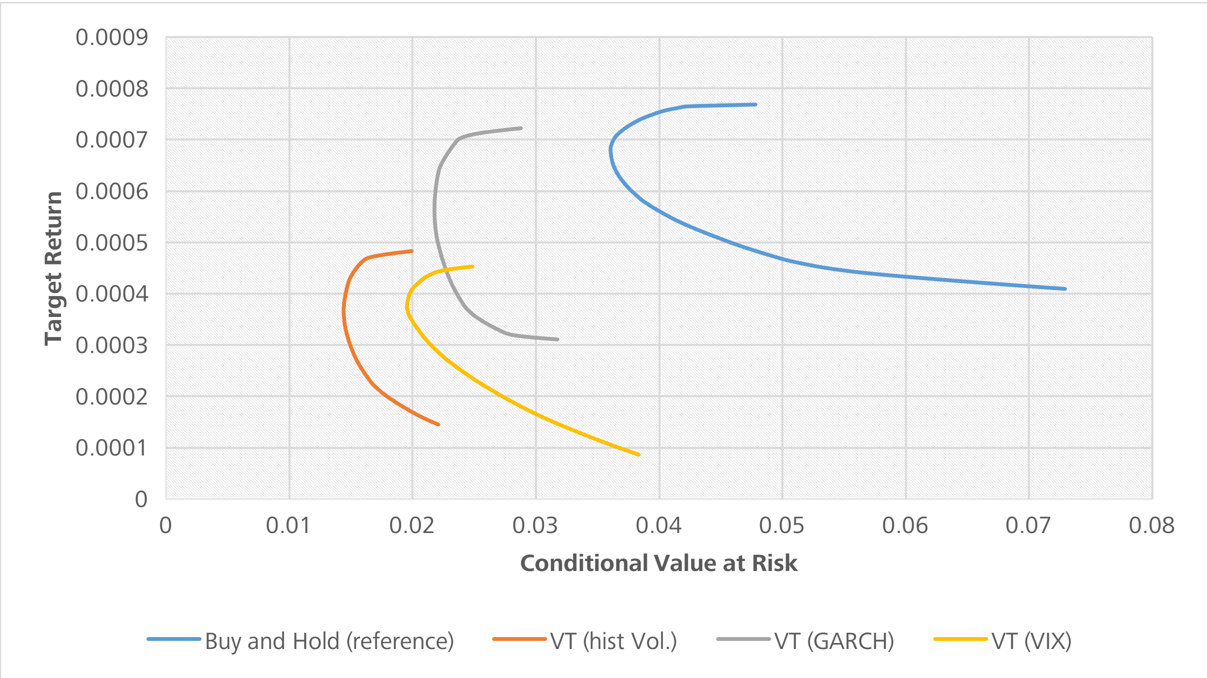
Within the VT estimators, the GARCH-based strategy shows the highest potential target returns. The lowest downside risk exposure can be achieved by using the historical volatility estimator. Subsequently, the subsamples are displayed to analyze potential differences across the REIT subclasses (see figures 5 – 11):

Figure 5: Efficiency frontiers within mean-$\mathbf{CVaR_{0.95}}$-framework (Office REITs)



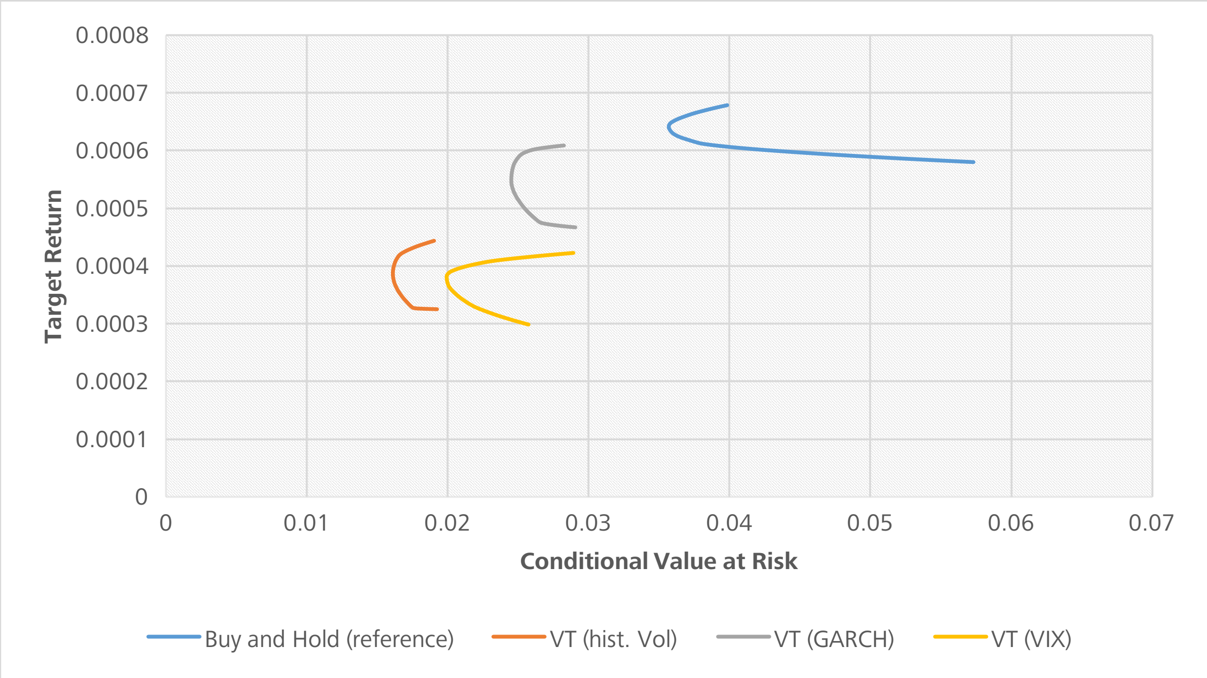
Source: Own presentation.

Figure 6: Efficiency frontiers within mean-$\mathbf{CVaR_{0.95}}$-framework (Retail REITs)



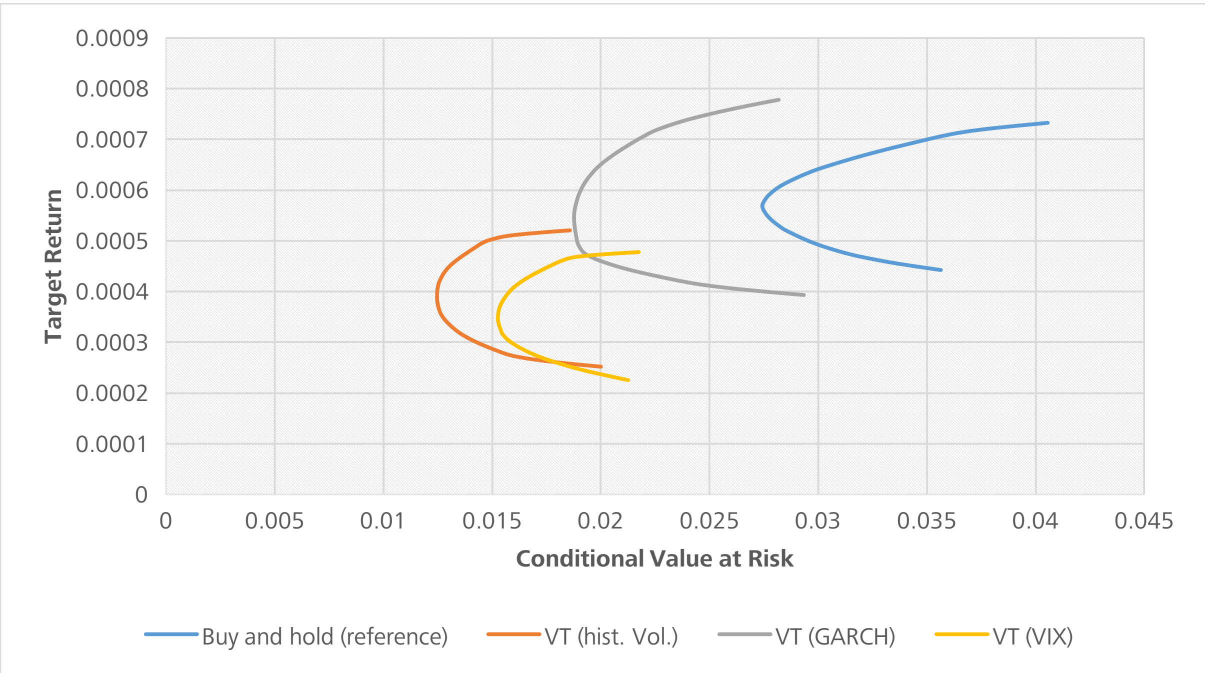
Source: Own presentation.

Figure 7: Efficiency frontiers within mean-$\mathrm{CVaR}_{0.95}$-framework (Industrial REITs)



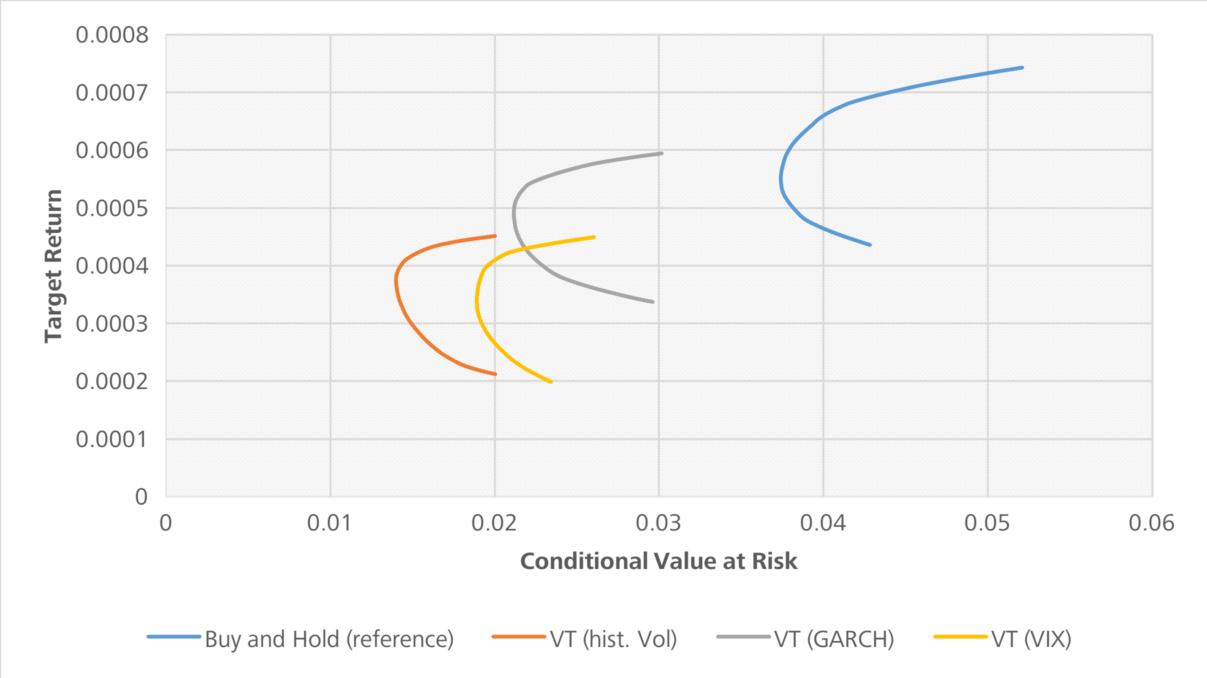
Source: Own presentation.

Figure 8: Efficiency frontiers within mean-$\mathrm{CVaR}_{0.95}$-framework (Residential REITs)



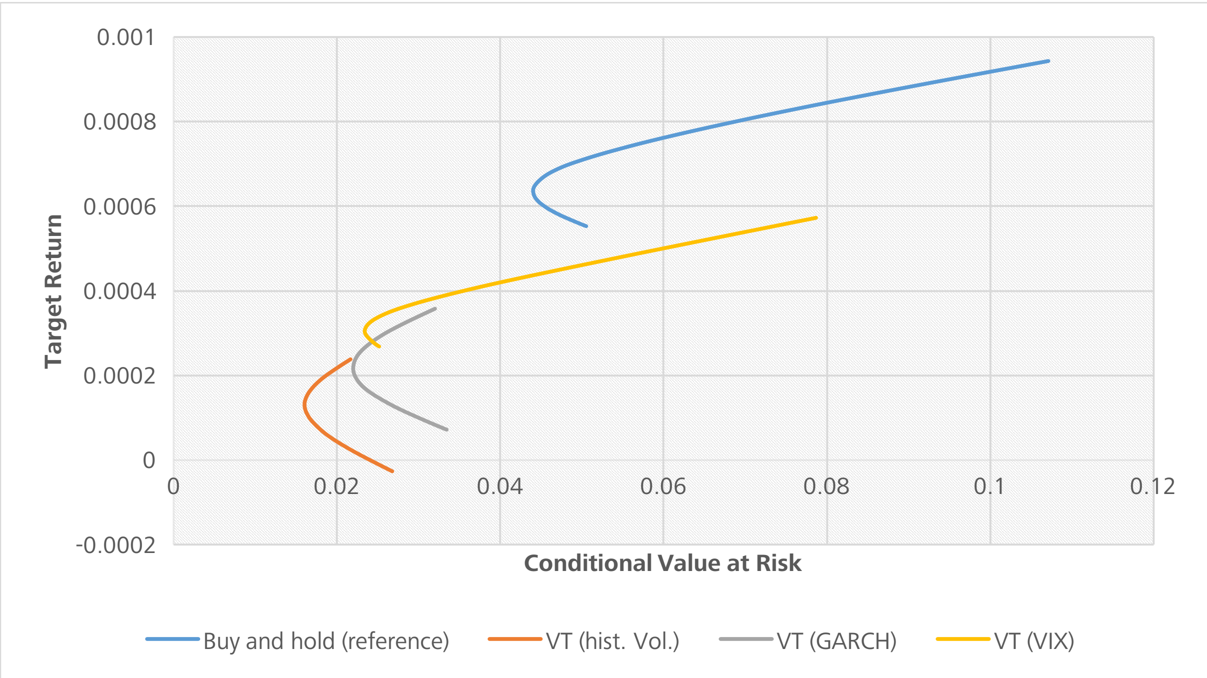
Source: Own presentation.

Figure 9: Efficiency frontiers within mean-$\mathrm{CVaR}_{0.95}$-framework (Diversified REITs)



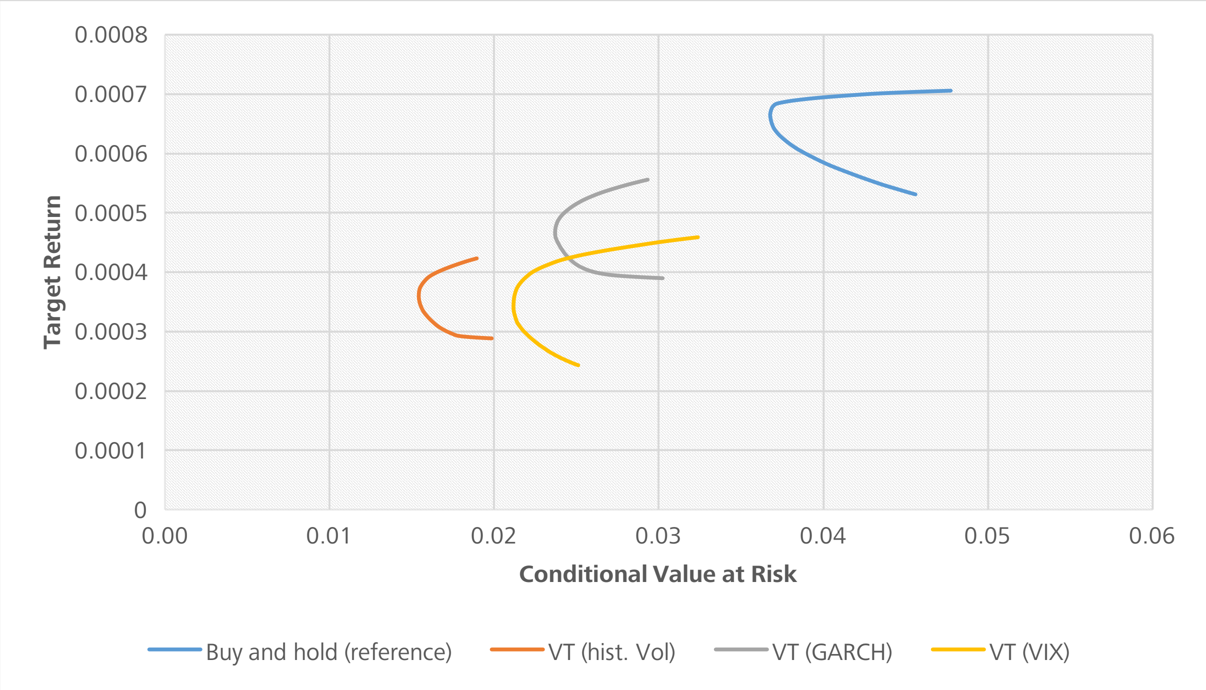
Source: Own presentation.

Figure 10: Efficiency frontiers within mean-$\mathrm{CVaR}_{0.95}$-framework (Lodging and Resort REITs)



Source: Own presentation.

Figure 11: Efficiency frontiers within mean-$\mathbf{CVaR_{0.95}}$-framework (Health Care REITs)



Source: Own presentation.

As revealed by the performance diagrams above, VT-based risk management of the equity REIT positions reduces the $CVaR_{0.95}$, since the efficiency frontiers for all samples offer solutions on the left of the buy and hold reference. The GARCH-based VT strategy generally provides the highest returns compared to its peers. Historical volatility as an estimator provides the lowest $CVaR_{0.95}$ solutions in all samples.[17] Thus, from an investor point of view, the historical volatility approach suits risk-averse investors best. Lodging and Resort REITs are, interestingly, most risk-aversely managed by using a VIX-based volatility targeting scheme. However, across all other samples, the VIX-based strategy is outperformed either on the return side by the GARCH-based VT or on the extreme downside risk side by the historical volatility estimator.

In addition to the graphical analysis, the maximum STARR of the efficiency frontiers reveal *numerical* proof of economic efficiency of the VT strategies. The figures show both interesting and puzzling results, since they are heterogeneous across the REIT types (see Table 15):

[17] Robustness checks for various timeframes regarding historical volatility estimation were tested, and results are consistent across different frames (30 – 60 days).

Table 15: Maximum STARR (Buy and Hold & VT (hist. Vol, VIX & GARCH))

Sample	*Investment Strategy*			
	Buy and hold	**VT (hist. Vol)**	**VT (VIX)**	**VT (GARCH)**
All REITs	0.025	0.037	0.028	0.036
Office	0.015	0.022	0.019	0.024
Industrial	0.018	0.025	0.019	0.024
Retail	0.019	0.029	0.021	0.030
Residential	0.022	0.035	0.026	0.033
Diversified	0.016	0.028	0.020	0.025
Lodging & Resorts	0.015	0.011	0.014	0.012
Health Care	0.018	0.024	0.018	0.021

Source: Own presentation.

Firstly and most importantly, the all REIT sample shows an increase in maximum STARR for all VT strategies compared to buy and hold. Within the VT strategies, the historical volatility measurement reveals the highest STARRs in five categories, whereas the GARCH-based approach maximizes the STARR for office and retail REITs.

Within the subsets, across office, industrial, retail, residential, and diversified REITs, all VT strategies outperform the reference. For health care REITs, the historical volatility and the GARCH-based estimation outperform the benchmark, whereas the VIX-based VT strategy does not show efficiency gains from VT. Interestingly, for lodging and resort REITs, the efficiency of the extreme downside risk protection does not hold. For the specified subclass, no VT strategy outperforms buy and hold. Within the VT strategies, the VIX-based strategy yields the highest maximum STARR for the specified subclass. A further analysis of the correlation of the VT return series matrices reveals that the correlations increase by using VIX-, or historical volatility-based VT (GARCH: -0.023, VIX: -0.001, hist. Vol.: -0.014).[18]

The potential reasons for the results and the heterogeneity across the equity REIT subsamples may mainly be the varying underlying risk factors for the subclasses and the differences in market predictability (Almudhaf & Hansz, 2018). Hoesli & Oikarinen (2012) prove the basic long-term relationship between equity REITs price volatility and their underlying assets. Thus, equity REITs are always integrated into the stock market, but are generally exposed to the risks associated with the usage types within the portfolio.

[18] Correlations for returns of the VT strategies are not reported.

Accordingly, some REIT classes such as office, industrial and retail are sensitive to different economic fundamentals (e.g. unemployment, GDP growth, consume sentiment), and thus react with less different price movements to extreme economic meltdowns such as in 2008. In contrast, health care, and self storage are seen as non-cyclical vehicles, since their income is relatively resilient to economic fundamentals. The specified subclasses generally provide smoother returns. Self storage income can even increase during recessions, due to lower space demand in residential markets, and higher demand for temporal storage of furniture. Risk factors of non-residential REITs are classically differentiated from residential REITs. The latter may also benefit from the cost of debt, since home ownership rates decrease, and thus residential space demand increases (Almudhaf & Hansz, 2018). These differences in return predictability and ex post volatility across the equity REIT subclasses can cause the heterogeneity of the results.

4.6 Conclusion, practical implications and further research

The present study analyzed the feasibility of VT strategies for minimizing extreme downside risks of US equity REIT positions. Accordingly, a two-stage procedure containing a back testing and subsequently a mean-$CVaR_\alpha$-portfolio-optimization was conducted. The latter expressed the extreme downside risk-return profiles of the strategies by calculating the maximum STARR.

The results reveal the following findings. Firstly, VT-based strategies generally reduce extreme downside risk, as illustrated by the position of the efficiency frontiers within the mean-$CVaR_\alpha$-diagram. Additionally, VT risk protection can also be evaluated as predominantly economically efficient for REIT investors, expressed by increased STARRs. The only equity REIT subclass to be consistently inefficient is lodging & resort REITs. Thus, the first hypothesis cannot be rejected.

Within the different volatility estimators, the lowest $CVaR_\alpha$ values are predominantly achieved by the historical volatility estimator, as revealed by optical inspection. The majority of samples reveals the highest efficiency for historical volatility measurement, followed by the GARCH approach. A VIX-based estimation yields the lowest efficiency. Thus, a trading strategy based on the implied volatility estimator of the S&P500 index appears to be problematic. From an investor point of view, the results increase doubts as to a sufficient capital market integration of equity REITs within the broader stock market. Accordingly, the second hypothesis needs to be rejected, since the VIX performs worse than the historical volatility estimator in seven of eight samples. In sum, the individual security volatility estimation seems to be more efficient than the modelling based on the entire stock market using the VIX.

The practical contribution of the empirical study is straight forward: Any risk-averse US equity REIT investor may apply VT in order to minimize extreme downside risk, since the $CVaR_\alpha$ of portfolios can be reduced. Additionally, investors can also improve the efficiency of their portfolios by using VT based on a GARCH model or on historical volatility.

Limitations of the present paper apply to the data sample, which analyzes only US equity REIT data. A comparison between equity and mortgage REITs or geographically at an international level, is not possible. VT studies across different REIT markets could provide insight into investment strategy usability across different geographic regions and also across market maturity levels (emerging vs. matured). Additionally, methodological limitations apply to the heterogeneity of the portfolio sizes, since the number of assets differs across the subsamples. Another point of potential criticism relate to the ignorance of transaction costs, as recently highlighted by Zakamulin (2019).

Further research could address other historical volatility measures such as Garman & Klass (1980), Parkinson (1980), Rogers & Satchell (1991) or Yang & Zhang (2000). Since the present study shows efficiency gains from GARCH-based VT, further research in the field using asymmetric models including exponential GARCH (Nelsen, 1991), threshold GARCH (Glosten et al., 1993) or asymmetric power GARCH (Ding et al., 1993) to estimate volatility may be beneficial. Harvey & Lange (2018) recently provided a comprehensive study for exponential GARCH modelling of broad US equities. Another field of interest may entail intraday VT strategies, since Zhou (2017) demonstrates higher explanatory power of these models for future return prediction. Models with higher data frequency may lead to further risk reduction potential. With increasing data availability the intraday volatility measurement has attracted greater interest. The authors highlights the need for HEAVY or GARCHX models, since high frequency data is less prone to market microstructures such as bid-ask-diffusions, discrete price observations or irregular trading.

4.7 Bibliography

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4.8 Appendix

Table 16: Correlation matrix (Office REITs)

	ARE	BXP	BDN	OFC	CUZ	HIW	KRC	CLI	SLG
ARE	1.000								
BXP	0.777	1.000							
BDN	0.724	0.768	1.000						
OFC	0.697	0.744	0.698	1.000					
CUZ	0.690	0.727	0.710	0.691	1.000				
HIW	0.761	0.811	0.773	0.753	0.761	1.000			
KRC	0.758	0.807	0.772	0.730	0.735	0.806	1.000		
CLI	0.745	0.793	0.773	0.729	0.759	0.815	0.793	1.000	
SLG	0.730	0.796	0.748	0.662	0.676	0.766	0.755	0.750	1.000

Source: Own presentation.

Table 17: Correlation matrix (Residential REITs)

	AIV	AVB	BRT	CPT	EQR	ESS	MAA	SUI	UDR	UMH
AIV	1.000									
AVB	0.805	1.000								
BRT	0.193	0.173	1.000							
CPT	0.798	0.842	0.152	1.000						
EQR	0.808	0.874	0.141	0.853	1.000					
ESS	0.748	0.840	0.159	0.795	0.826	1.000				
MAA	0.749	0.801	0.183	0.800	0.800	0.767	1.000			
SUI	0.634	0.654	0.181	0.668	0.639	0.648	0.652	1.000		
UDR	0.796	0.829	0.140	0.821	0.835	0.803	0.781	0.669	1.000	
UMH	0.243	0.221	0.108	0.238	0.212	0.237	0.225	0.293	0.242	1.000

Source: Own presentation.

Table 18: Correlation matrix (Industrial REITs)

	DRE	EGP	FR	PLD	PSB
DRE	1.000				
EGP	0.733	1.000			
FR	0.676	0.640	1.000		
PLD	0.824	0.745	0.705	1.000	
PSB	0.694	0.697	0.606	0.700	1.000

Source: Own presentation.

Table 19: Correlation matrix (Retail REITs)

	AKR	ADC	CBL	NNN	FRT	KIM	MAC	PEI	RPT	O	REG	BFS	SPG	SKT	TCO	WRI
AKR	1.000															
ADC	0.489	1.000														
CBL	0.603	0.491	1.000													
NNN	0.651	0.586	0.620	1.000												
FRT	0.669	0.565	0.672	0.748	1.000											
KIM	0.684	0.541	0.703	0.731	0.811	1.000										
MAC	0.643	0.528	0.743	0.675	0.742	0.770	1.000									
PEI	0.636	0.496	0.726	0.640	0.662	0.721	0.713	1.000								
RPT	0.573	0.468	0.561	0.538	0.574	0.606	0.590	0.575	1.000							
O	0.643	0.580	0.606	0.786	0.784	0.768	0.685	0.644	0.539	1.000						
REG	0.682	0.570	0.697	0.753	0.825	0.844	0.778	0.720	0.595	0.771	1.000					
BFS	0.614	0.500	0.554	0.639	0.639	0.662	0.605	0.596	0.535	0.645	0.661	1.000				
SPG	0.662	0.552	0.702	0.741	0.822	0.849	0.763	0.687	0.571	0.780	0.812	0.650	1.000			
SKT	0.620	0.489	0.599	0.663	0.697	0.692	0.630	0.608	0.520	0.665	0.688	0.603	0.691	1.000		
TCO	0.644	0.535	0.689	0.702	0.778	0.788	0.746	0.684	0.576	0.734	0.784	0.631	0.797	0.663	1.000	
WRI	0.688	0.577	0.713	0.749	0.809	0.857	0.775	0.728	0.628	0.774	0.844	0.669	0.823	0.698	0.785	1.000

Source: Own presentation.

Table 20: Correlation matrix (Diversified REITs)

	ALX	OLP	LXP	VNO	WRE
ALX	1.000				
OLP	0.417	1.000			
LXP	0.550	0.513	1.000		
VNO	0.592	0.518	0.729	1.000	
WRE	0.545	0.485	0.718	0.777	1.000

Source: Own presentation.

Table 21: Correlation matrix (Health Care REITs)

	HCP	HR	LTC	NHI	OHI	UHT
HCP	1.000					
HR	0.785	1.000				
LTC	0.515	0.534	1.000			
NHI	0.549	0.543	0.422	1.000		
OHI	0.503	0.502	0.430	0.412	1.000	
UHT	0.616	0.655	0.508	0.509	0.436	1.000

Source: Own presentation.

Table 22: Correlation matrix (Lodging & Resorts REITs)

	HPT	IHT
HPT	1.000	
IHT	-0.021	1.000

Source: Own presentation.

5 AR-GARCH-EVT-Copula for Securitized Real Estate: An approach to improving risk forecasts?

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Journal of Property Research (published)

Abstract

This study presents a quantitative analysis of the so-called AR-GARCH-EVT-Copula model aimed at forecasting risk metrics for multi-asset portfolios, including securitized real estate positions. The model incorporates a non-linear dependence structure and time-varying volatility in asset returns. Accordingly, an empirical study using data from six major global markets is carried out. The approach is applied in order to forecast risk metrics, in comparison to classical methods like historical simulation and variance-covariance models. Forecasts are then compared with realized returns, in order to calculate hit sequences and conduct statistical interference on the respective models. It is empirically shown that, the AR-GARCH-EVT-Copula model provides a superior forecast concerning risk metrics. This is mainly due to the usage of copulas, allowing us to individually model the dependence structure of random variables. Back testing and test results confirm the superiority of our model in comparison with classic methods such as historical simulation and Variance-Covariance approach. The decomposition of the univariate and multivariate models of the target model reveal the necessity to allow for high order and thus long-lasting autoregressive modelling as well as asymmetric tail dependence and rotated copulae across different portfolios.

5.1 Introduction

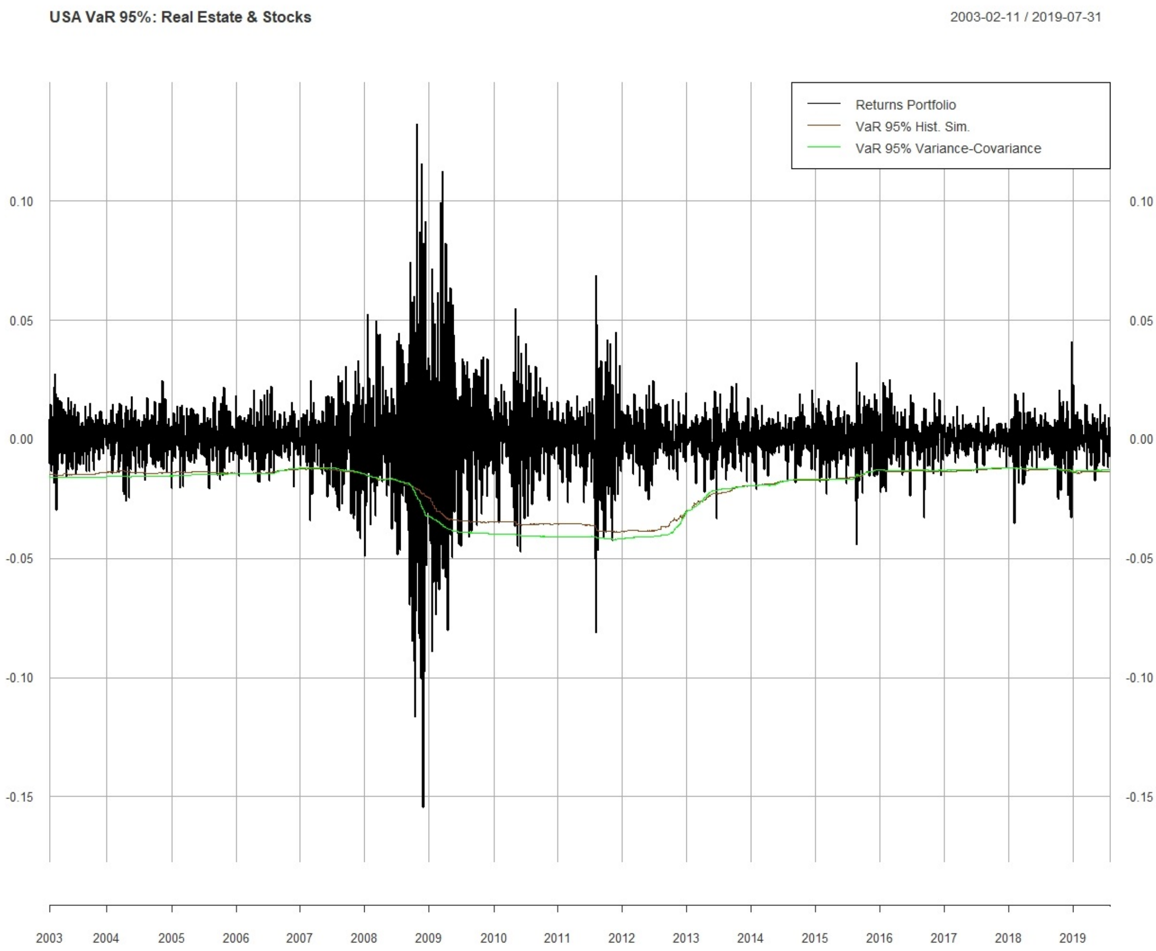
The risk modelling of investment positions has attracted larger interest, since the global financial crises (GFC) in 2008 painfully demonstrated the vulnerability of international financial markets. Central issues emerging from this turbulent period have included the contagion effects of direct real estate markets and corresponding mortgage positions towards other asset classes such as equities, which were affected by the triggered macroeconomic downturn (Hui & Chan, 2013).

Subsequently, institutional debt and equity investors have both experienced a tangible tightening of the regulatory framework, including Basel III (and its addendum know as Basel III reform package) as well as Solvency II. Especially banks and insurance companies are facing increased legal obligations relating to their internal price risk models, in case they are holding public equity positions, which are exposed to the risk of market price changes (Ergen, 2015). Risk measures for price risk such as the Value at Risk (VaR_α) or Conditional Value at Risk ($CVaR_\alpha$) are typically underestimated and capital requirements insufficient, if they are computed on the assumption of normality and independence, while the returns of the multi-asset portfolios are in reality leptokurtic, and entail skew and autocorrelation (Liow, 2008). Rossignolo et al. (2012) advise an application of extreme value theory (EVT) as a potential response to the abovementioned regulatory challenge, including the correct modelling of skewed and fat-tailed returns.

Accordingly, the potential to model the data of non-normal returns, as well as the dependence structure of these positions so as to estimate joint extreme value losses, is of particular interest for the risk management of institutional investors. The classic approach of using linear concepts such as the Bravais-Pearson correlation coefficient for original time series data does not provide information about the structure and assumes an elliptical joint distribution of the assets (Wu & Lin, 2014).

With regard to the price risk of securitized real estate, however, dependence structure modelling towards other asset classes is scarce. Dependence modelling of securitized real estate either only discusses the structures within the specified asset class itself (Knight et al., 2005, Goorah, 2007), or with other asset classes, but without prior univariate AR-GARCH-EVT modelling (such as Dulgerov, 2009). Figure 12 shows the importance of a correct model to measure VaR^α as well as $CVaR^\alpha$ especially during times of crises.

Figure 12: VaR (α = 0.95) estimates for Real Estate–Stocks portfolio (US)



Notes: Figures for VaR 99%, CVaR 95% and CVaR 99% for real estate-stocks and real estate-bonds portfolios are available upon request. All of these figures look similar to this figure concerning the hits of historical simulation and variance-covariance models with the return series.

Source: Own presentation.

Historical simulation and variance-covariance are two conventional tools for measuring VaR^{α} and $CVaR^{\alpha}$. Figure 12 shows the problem of the currently applied models, because the models for the price risk of the portfolios are clearly failing to provide accurate price risk forecasts. Thus, the standard methodology is not able to make valid statements about the actual risk exposure, leading to potentially wrong risk bearing capabilities in terms of equity underlying. Hence, the need for a better model is obvious. This necessity seems to be even more important when considering, that extreme observations are particularly common in securitized real estate return series, due to the integration in direct markets and potential herding behavior due to drastically changing return expectations (Hoesli & Oikarinen, 2012).

The real estate literature has not been linked to the body of literature applying AR-GARCH-based univariate modelling and EVT to account for heteroscedastic and autocorrelated time series, as originally proposed by McNeil & Frey (2000). The connection between the abovementioned bodies of literature, which leads to the so-called *AR-GARCH-EVT-Copula* approach and its subsequent empirical study of the feasibility of enhancing price risk forecasting using the specified approach evaluation is among other preliminary results, the main motivation of the present study.

Accordingly, the central research question is whether the AR-GARCH-EVT-Copula approach can improve price risk forecasts for investors holding portfolios containing securitized real estate. Therefore, the study sets up the AR-GARCH-EVT-Copula model to account for the abovementioned statistical challenges associated with financial time series data. Subsequently, the study models the dependence structures, and forecasts the VaR^{α}. And the $CVaR^{\alpha}$. based on these univariate and multivariate models. Finally, a back-testing procedure compares forecasts with real returns to evaluate the model in comparison to known approaches such as variance-covariance and historical simulation.

Thus, the paper contributes to the existing real estate literature in several ways. Predominantly, a methodologically innovative application of the AR-GARCH-EVT-Copula technique including price risk metric forecasting is provided. To the best of the authors' knowledge, the approach has not yet been applied to multi-asset portfolios which include securitized real estate.

This study is structured as follows in order to make the contribution described above: Section 2 reproduces the most important related literature and derives the hypothesis. Section 3 explains the methodological approach. Section 4 describes the data and the ensuing section presents the results in terms of the risk forecast accuracy and model errors across various copula types. Section 6 concludes and outlines further research.

5.2 Literature review and hypothesis derivation

The following bodies of literature are relevant as framework for the present study, namely: Stylized facts of financial time series and the underlying economic drivers which cause the problematic statistical features (with special focus on securitized real estate, but also for stocks and bonds), univariate conditional mean and volatility modelling including EVT and the corresponding standardization procedures of the data, dependence modelling and the evaluation possibilities of risk forecast models, as well as the subsequent risk management implications. The present literature review is supposed to outline the actual problem set as well as existing studies in the field to illustrate the research gap. The subsequent methodology section will then outline the actual models in a more mathematical and formal way, including the equations of the approach.

The fundamental driver for the present study is the body of literature exploring stylized facts about the returns of stocks, bonds and securitized real estate. Primarily, stylized facts of daily securitized real estate returns are important for the present study. As shown by Hoesli & Oikarinen (2012), the specified returns are predominantly a function of the returns of the vehicles' underlying assets, and explicitly not only of the overall stock market. Accordingly, the features of direct property markets are highly relevant for the application of a price risk forecasting methodology for securitized real estate. Since direct real estate returns are widely known for non-normality (Byrne & Lee, 1997; Young et al., 2006; Richter et al., 2011), these underlying assets pass their statistical return characteristics through the securitizing vehicle.

Additionally, direct property markets also show autocorrelation of their returns, especially for appraisal-based capital value returns. In this context, various studies have shown the autocorrelation and thus predictability of direct real estate returns, denying the classic assumption of market efficiency or random walk behavior, empirically based on the specified returns (Wheaton et al., 1999; Payne & Sahu, 2004; Coleman & Mansour, 2005). Reasons for this are relatively high transaction costs, low turnover volumes, tax-related issues, asymmetric information and the heterogeneity of the commodity itself (Schindler, 2010). Just like the stylized fact of non-normality, autocorrelation is also passed through the securitizing vehicle, as empirically shown by e.g. Kuhle & Alvayay (2000). In this context, the authors differentiate between short- and long-term autocorrelation. The main reason for short-term autocorrelation in daily securitized real estate returns is assumed to arise mainly from differing information availability across investors. Long-term autocorrelation of daily returns is mainly caused by the long-lasting nature of cash flows from the leases of the underlying properties. Thus, a clear relationship between the characteristics of the held real estate assets and the resulting stylized facts of the return series of the securitizing vehicle can be identified.

At last and in addition to non-normality and autocorrelation, the volatility of securitized returns needs to be addressed. The central finding in the existent body of literature is the heavy volatility clustering with differing variance across time (Cotter & Stevenson, 2006; Jirasakuldech et al., 2009). From an economic point of view, Letdin et al. (2019) review the underlying mechanisms for this phenomenon. The authors name the low transparency and high capital volumes but also potentially suddenly changing information about property markets and investments as decisive driver for simultaneous investor decisions. These synchronic movements of investors are causing the volatility clustering. Based on these stylized facts, it can be concluded, that a feasible price risk forecasting model for any portfolio, containing securitized real estate positions needs to be able to account for the non-normality, autocorrelation and volatility clustering of the return series.

In addition to securitized real estate, stocks and bonds are the typical investment targets for multi-asset real estate investors seeking diversification (e.g. Hoesli et al., 2003). For market data concerning stocks, studies analyzing the distributional characteristics date back to the 1960, doubting classic Gaussian assumptions (Mandelbrot, 1963; Fama, 1965). Regarding normality, a large body of literature has empirically shown the existence of negative skew and leptokurtosis and additional fat tails (e.g. Officer, 1972; Bekaert & Harvey, 1998; Harris & Kücüközmen, 2001). Studies cite overreaction and herding behavior as a potential explanation (de Bondt & Thaler, 1985). Consigli (2002) also highlights the heterogeneity of financial markets, since they are especially prone to country- and period-specific risk, causing heavy intertemporal autocorrelation and the associated volatility clustering.

Bond return data is also known for skewed and leptokurtic returns (Rachev et al., 2003, Wu & Lin, 2014). Just as for the previously described equity returns, bond returns across various maturity levels are not normally distributed and are especially fat tailed, which are methodologically explored by means of highly significant kurtosis parameters of stable distributions (Gabriel & Lau, 2014).

Summarizing the existent literature for the cross-section of assets, return series are highly questionable regarding Gaussian assumptions. The named stylized facts cause biased related statistical measures and false asset allocation (Dittmar, 2002). In addition, falsely modelled tails, assuming perfectly elliptical asset returns, cause tail risk estimation and its hedging to fail which is highly important for strategic portfolio management.

Based on these obstacles of non-normality, autocorrelation and heteroscedasticity of financial time series data, McNeil & Frey (2000) have introduced the AR-GARCH-based standardization of returns, in order to account for the outlined problematic stylized facts.[19] Within the cited body of literature for univariate volatility modelling, two central methodical questions are of interest: degrees of autoregressive components of the conditional mean model and the distribution assumption of the error terms for the conditional volatility model.

First of all, the autoregressive and moving average components need to be specified. Interestingly, the literature agrees on an autoregressive component (see Rocco, 2014 for an overview). Regarding the distribution of the errors of the conditional volatility model, normally- and (skewed) t-distributed error terms are options. Skewed t-distributions have largely shown improvements in VaR^{α} predictions (Küster et al., 2006; Bali & Theodossiou, 2008; Mabrouk & Saadi, 2012).

Based upon the conditional volatility model of McNeil & Frey (2000), the decomposition of the distribution to model fat tails is necessary. Therefore, EVT is applied to model the observations over a threshold in the tails, assuming them to follow a Generalized Pareto Distribution (GPD). In combination with the univariate GARCH modelling, the resulting combined GARCH-EVT approach has been used by various studies (Bhattacharyya & Ritolia, 2008; Chan & Gray, 2006; Deng et al., 2011). The GARCH-EVT-based univariate estimation of tail also entails two crucial advantages: It is

[19] As well as EVT application to the fat tails, which will be reproduced in detail below.

based on well-established statistical theory and also enables a parametric estimation (Karmakar, 2017). With regard to the goal of the present study to forecast risk metrics more precisely, Bao et al. (2006), Küster et al. (2006), Bali (2007) are examples of enhanced risk metric forecasting performance, due explicitly to EVT application to the tails. The so-far described procedure accounts for standardizing the data, and generating independently, identically distributed observations. Classic approaches such as variance-covariance or historical simulation do not apply the named procedure to the original return series. Thus, the return series of these models still yield the specified issues and cause bias to the risk metrics.

Subsequently, the need to model the multi-asset dependence arises. The main economic reason for potentially non-linear tail dependence is the similarity of the underlying macroeconomic drivers for property market and returns of the broader stock market from industrial production etc. (Christoffersen et al., 2014). Traditional linear correlation models such as the widely adopted Bravais-Pearson's coefficient, however, only measure the degree of explicitly linear dependence. It needs to be highlighted that variance-covariance models for forecasting risk metrics exactly assume constant and linear dependence across time. Accordingly, these models provide no information about the structure of the dependence.

From an empirical point of view, especially the additional proposition of Hoesli & Oikarinen (2012) regarding real estate's integration into the broader stock market has gained attention, because equity and securitized real estate returns are assumed to show heavy tail dependence for the outlined reasons. Empirical findings of various studies confirm this tail dependence of securitized real estate and stocks (Huang & Zhong, 2013; Yang et al., 2012).

The abovementioned reasons have motivated researchers to develop alternative concepts of dependence structure modelling, as firstly proposed by Sklar (1959), and introducing copula functions. Convening the usage of the correct copula, authors like Kole et al. (2007) and Hurd et al. (2007) find that the goodness-of-fit of an Archimedean Student-t as well as other copulae is superior to that of an elliptical Gaussian copula, for the reasons given of simultaneous heavy downturns and thus left tail dependence.[20] The described tail dependence for simultaneous extreme losses of securitized real estate and stocks in the same nation are a direct consequence of the similarity of risk factors such as fundamental macroeconomic drivers. This detail is especially crucial for risk management purposes, since the copula function is supposed to correctly explicitly model the lower tail or asymmetric tail dependence respectively.

The usage of copulae in real estate literature is scarce, although existing (Goorah, 2007; Dulgerov, 2009). Knight et al. (2005), as well as Chang et al. (2011), have adopted a non-linear modelling of

[20] Tail dependence of the individual copula families will be discussed in detail below.

multi-asset portfolios including real estate.[21] Nonetheless, the authors do not apply EVT to the univariate return distribution before modelling the bivariate tail dependence. However, they find heavy asymmetric tail dependence, especially in downturn markets. Since they find time-variant dependence, approaches which model dependence as constant across time are expected to perform worse in comparison. Hoesli & Reka (2013) found the same time-variance of the co-movement, especially for the tails of returns of securitized real estate and stocks. The associated asset class of infrastructure equities was analyzed in a closely-related study by Chakkalakal et al. (2018). It should be explicitly emphasized, that the named articles broadly assess parameters of the copulae, without any risk metric forecasting context.

Lastly, the methodical approach used to evaluate improvements to risk models is important. In this field, the literature has mainly focused on back testing of risk metric forecasts (summarized by Du & Escanciano, 2017). Essentially, back-testing procedures estimate forecasts using the risk model and compare these values with true realizations, as conducted by Wu & Lin (2014) or Sahamkhadam et al. (2018). Whenever the model underestimates the risk metric for the period to be forecasted, a so-called "hit" occurs. These hits are collected in a binary vector and compared to the confidence level of the model (Kupiec, 1995 and Christoffersen, 2004). Normally, new approaches to forecast risk metrics are compared to benchmark models of historical simulation and variance-covariance. Based on the abovementioned literature, the following hypothesis is derived as the foundation for our own empirical study of the AR-GARCH-EVT-Copula: The AR-GARCH-EVT-Copula approach to estimating forecasts of risk metrics generates more accurate risk metric forecasts of portfolios containing securitized real estate, in comparison to classic approaches such as historical simulation or variance-covariance. This hypothesis is formulated, because risk models for multi-asset portfolios which account for autocorrelation, skew and fat tails, as well as non-linear dependence, are assumed to outperform their classic counterparts.

5.3 Methodology

The present study assesses the feasibility of the AR-GARCH-EVT-Copula approach to improving the forecasts for the VaR^{α}. of multi-asset portfolios, which include securitized real estate. Based on the above mentioned literature review, the methodology is supposed to describe the actual methodological translation to set up the AR-GARCH-EVT-Copula model. As benchmark methodologies, the study applies classic variance-covariance and historical simulation methods, which are not extensively discussed here. However, the basic idea of price risk forecasting for

[21] For a more technical approach on the details of the methodology in the broader stock market, we recommend the study of Wei & Zhang (2004).

financial portfolios is the anticipation of future return changes based on available univariate or multivariate information such as past returns or co-movements of the portfolio constituents.

Essentially, our AR-GARCH-EVT-Copula methodology of interest is an algorithm, which refits univariate and multivariate models to rolling windows of time series data, in order to forecast the VaR^{α}. for the day ahead of the analyzed part of the data by simulating return data for the profit-and-loss function (P&L). Since the forecasting of portfolio returns and subsequent risk metric calculation require univariate modelling of the individual return series as well as the dependence structure, these steps are presented in detail.

The univariate AR-GARCH modelling for each window of the return time series containing daily log returns $r_t, t \epsilon [0, T]$ can be summarized by the following set of equations:

$$r_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t \tag{22}$$

$$\mu_t = \mu + \sum_{i=1}^{s} \gamma_i r_{t-i} \tag{23}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{24}$$

$$z_t \sim skewed - t(0,1) \tag{25}$$

The return equation (1) is a function of the conditional mean and an error component ε_t, which can be rewritten as the product of the conditional volatility and the error z_t. The conditional mean equation (2) for μ_t yields past returns r_{t-i}, and a constant term μ. Thirdly, the conditional variance σ_t^2 is modelled by equation (3) as a function of past variance σ_{t-i}^2 as well as a quadratic error term ε_{t-i}^2. Lastly, the error terms of the return equation (1) are assumed to follow a skewed t-distribution for the outlined reasons of leptokurtic return behavior, as expressed by equation (4).

The order for the AR models are adjusted for each rolling window of 1000 observations by testing for the minimum Akaike Information Criterion (AIC) up to order 5. For the conditional variance model, the study follows Hansen & Lunde (2005) or Wang et al. (2010) by applying a GARCH(1,1) model.

Conditional on the available information of each rolling window, the model parameters of $\hat{\lambda} = (\hat{\mu}, \hat{\gamma}, \hat{\omega}, \hat{\alpha}, \hat{\beta})$ are estimated. Additionally, the one day ahead conditional mean, as well as conditional volatility are estimated, denoted by $\hat{\mu}_{t+1}$ and $\hat{\sigma}_{t+1}$ for $t \epsilon [1000, T-1]$. Thus, the first 1000 days of the data set represents the burn-in sample, for which no risk metrics are calculated. The first day for which the study estimates risk forecasts is the 1001st day. The estimates are saved for the later simulation of the P&L function of the one-day-ahead returns.

More importantly, the estimated standardized residuals are extracted to model the dependence, since they are expected to satisfy the assumption of independent and identical distribution, so as to produce unbiased estimates:

$$\hat{z}_t = \frac{r_t - \hat{\mu}_t}{\sigma_t} \tag{26}$$

Nonetheless, these standardized residuals may still exhibit fat tails, which can be modeled directly by EVT, in particular by the peak-over-threshold method assuming tails to follow a GPD, proposed by McNeil et al. (2005). In choosing the correct threshold, there is a trade-off that should be noted. If selected too low, there may not be enough data points in the tails to ensure an unbiased estimation, and some data points which are relatively far from the actual kernel distribution are not considered in the tails. By introducing a lower threshold, more observations from the center of the distribution are introduced into the series we want to cut off which makes the estimator less volatile but increases the bias of a tail distribution which should consist of extreme observations. Following DeMelo Mendes (2005), we set the threshold to the 10% quantile for the left part and to the 90% quantile for the upper part of the distribution. For a further assessment of the correct threshold selection, mean excess functions and so-called Hill plots were considered, as well. (Wang et al., 2010).

Modelling the standardized residuals is achieved by using the GPDs for the marginal distributions of the tails, in combination with the empirical distribution for the interior kernel. Equation (6) illustrates the newly created distribution:

$$F(z)\begin{cases} \frac{n_L}{n}\left\{1+\xi_L\frac{(z-u_L)}{\psi_L}\right\}^{-1/\xi_L} & z < u_L \\ \phi(z) & _L < z < u_R \\ 1-\frac{n_R}{n}\left\{1+\xi_R\frac{(z-u_R)}{\psi_R}\right\} & z > u_R \end{cases} \tag{27}$$

where u_L, and u_R are the lower and upper threshold respectively. n denotes the overall number of observations of z and n_L, n_R represent the number of observations that are in excess of the thresholds. Scale (ψ) and shape (ξ) are then estimated via maximum likelihood. $\phi(z)$ represents the empirical distribution of the Gaussian kernel. The specified procedure completes the univariate modelling and preparation of standardized residuals for each of the $T - 1000$ rolling windows.

Based upon the described univariate modelling, the second step is to model the multivariate relationship, since the simulation of portfolio returns requires information about the dependence structure of the assets. As outlined, various economic factors cause dependence structures to be non-linear.

Thus, the present study uses copula functions to model the dependence, in contrast to classic measures like the Bravais-Pearson correlation coefficient. A copula is a function that couples a multivariate distribution function to its univariate marginal distributions, and does not require any assumptions on the selection of the distribution function, as introduced by Sklar (1959) and Sklar (1973).

Formally, a copula function C can be expressed as a link of the marginal distributions between the random variables, or in this specific case as a bivariate copula of the standardized residuals, $\hat{z}_{i,t}$, for real estate positions and stocks or bonds:

$$F\left(\hat{z}_{1,t}, \hat{z}_{2,t} \vee \hat{z}_{3,t}\right) = C\left(F_1\left(\hat{z}_{1,t}\right), F_2\left(\hat{z}_{2,t} \vee \hat{z}_{3,t}\right)\right), \text{ for } \hat{z}_1, \hat{z}_2, \hat{z}_3 \quad (28)$$

C is a bivariate distribution function containing the marginals $F_1$and F_2 of the two assets in the portfolio of interest. If F_i is the joint distribution function of a random vector with continuous marginals of F_1 and F_2, then C is unique and given by:

$$C(p_1, p_2) = F\left(F_1^{-1}(p_1), F_2^{-1}(p_2)\right), \text{ for all } (p_1, p_2) \in [0,1]^n \quad (29)$$

There are mainly two main families of copulae, namely elliptical and Archimedean, containing a variety of parametric copula types. As noted by Nelsen (1999), Archimedean copulae allow for asymmetry in the tail dependence. Typical examples of such asymmetric copulae are the Frank, Gumbel, BB1, BB2 and BB7. As described above, the literature has shown the potential of asymmetric dependence, especially in the tails between securitized real estate and stocks or bonds respectively. Accordingly, Archimedean copulae are incorporated into the modelling.

In this context, different copulae also allow for different tail dependence. Each copula family has its own formula to derive the lower and upper tail dependence. If the two tail dependences are equal, there is symmetrical behaviour, which, due to the abovementioned reasons is rather unexpected.

For example, the common Gaussian copula has zero tail dependence, whereas the asymmetrical Gumbel copula has right or upper tail dependence, but zero left or lower tail dependence. Other copulae like BB1 and BB7 have tail dependence of different, non-zero, strength (e.g. Gumbel (1960), Clayton (1978), Frank (1979), Joe (1993 & 1997) & Nelsen (1999)).

For each rolling window and its pair of standardized residuals, the named copulae are fitted to estimate the model parameters following the inference-for-margins (IFM) approach proposed by Joe and Xu (1996). The copula, which shows the lowest AIC for the respective window is chosen as dependence structure model. In this study, copulae with one and two parameters as well as their 90°, 180° and 270° rotated peers are tested (see Table 28 for the full list of the 28 copula types).

Based on the above pattern, the methodology models the individual asset returns as well as the dependence structure between them for each window, as a foundation for the simulation of the one-day-ahead forecast of returns. Nonetheless, one may wonder how the dependence modelling of standardized residuals translates into return forecasts. Here, the decisive methodological step is carried out: Probability integral transformation (PIT) of the standardized residuals.[22] This transformation uses random numbers from the multivariate distribution. Subsequently, the correlation matrix of the copula is disintegrated, and the residuals for the univariate model are then generated using the inverse of the joint distribution, namely F_i^{-1}.This simulation of the one-day-ahead residuals out of the named distribution is carried out M times to generate the simulated residuals, $\hat{z}_{i,t+1}$. For the simulation, 10,000 return scenarios from the estimated AR-GARCH-EVT-Copula model are generated. Notably, to check whether the number of simulations is sufficient enough, the simulation was also performed 50,000 times. The results were not significantly different, in fact, they were the same. These residuals are then incorporated into equation (1), as expression for the individual returns of the two assets of interest:

$$\hat{r}_{i,t+1} = \mu_i + \hat{z}_{i,t+1}\hat{\sigma}_{i,t+1}, \qquad i = 1,2. \tag{30}$$

Based on the simulated returns, the equal portfolio weights are introduced to calculate the portfolio returns of the hypothetical two-asset portfolios. Given these weights, risk metrics for the simulated portfolio-return P&L distribution can be calculated and compared with the actually observed returns, in order to measure the accuracy of the forecast. For each portfolio, the forecasted VaR_{t+1}^{α} and $CVaR_{t+1}^{\alpha}$ for any confidence level α can be derived from the P&L of the simulated returns.

Lastly, the specified risk metrics are back-tested. Since, in comparison with the $CVaR^{\alpha}$, the VaR^{α} is known to be elicitable, different procedures have to be applied.[23] For the VaR_{t+1}^{α}, violation and independence-based tests are carried out. In order to conduct these tests, the VaR_{t+1}^{α} values from the AR-GARCH-EVT-Copula model and the classic historical simulation and variance-covariance model and are compared to the actual return series, so as to calculate so-called hit sequences (or "violations"), I_{t+1}. These sequences represent the model violations, namely the negative exceedance of realized returns over risk-metric forecasts:

$$I_{t+1}(\alpha) = \begin{cases} 1, if\ r_{t+1} < -VaR_{t+1}^{\alpha} \\ 0, if\ r_{t+1} > -VaR_{t+1}^{\alpha} \end{cases} \tag{31}$$

[22] The transformation methodology differs across the copula families; nonetheless, the basic idea is consistent. See Wang et al. (2010) for more details on differences for elliptical and Archimedean copulae.

[23] Accordingly, the approaches to back-test the $CVaR^{\alpha}$ are still subject to debate. See Nolde & Ziegel (2017) and Acerbi & Szekely (2017) for a detailed discussion.

Firstly, a binominal test is applied to $I_{t+1}(\alpha)$. The abovementioned hit sequence should be a Bernoulli-distributed random variable with probability (α) and the number of observations for which risk forecasts are calculated (n):

$$I_{t+1}(\alpha) \sim B(n, \alpha) \tag{32}$$

Additionally, the Kupiec test is conducted. In order to conduct statistical inference on the specified distributional property of the hit sequence and its accuracy, the test statistic $K \sim \chi(1)$ is calculated in order to conduct a two-sided test of the null hypothesis, regarding whether the hit sequence follows the specified distribution (Kupiec, 1995):

$$K = -2\ln[(1-p)^{n-m}p^m] + 2\ln\left[(1 - {}^{m}/_{n})^{n-m}({}^{m}/_{n})^m\right] \tag{33}$$

In equation (12), p denotes the assumed probability of occurrence, or α respectively, m the number of hits of the model and n the number of tests. Thus, the methodologies outlined above test whether the AR-GARCH-EVT-Copula model or historical simulation and variance-covariance provide a statistically sound modelling of the hit sequence for the VaR_{t+1}^{α} forecasts.

Additionally, the independence-based test of Christoffersen (1998) is applied. In contrast to the violation-based Bernoulli and Kupiec tests, this procedure not only measures the number of hits, but also their occurrence across time. Since the null hypotheses address specific properties of independence like exceedances not clustering, or loss quantiles not being autocorrelated, independence tests are more relevant for deciding whether the corresponding model is superior. Therefore, the null hypothesis states that the occurrence of violations $I_{t+1} = 1$ cannot be described by a first-order Markov Chain:

$$P(I_{t+1} = 0 | I_t = 0) = P(I_{t+1} = 0 | I_t = 1) = 1 - \alpha \tag{34}$$

For the $CVaR_{t+1}^{\alpha}$ on the other hand, a zero mean test is conducted, as proposed by McNeil et al. (2005). The test essentially assesses whether the excess loss component, given that a hit of the VaR_{t+1}^{α} occurred ($I_{t+1} = 1$), has a mean of zero. The procedure can be interpreted as a standard t test under the assumption of i.i.d.:

$$S = (r_{t+1} - CVaR_{t+1}^{\alpha} | I_{t+1} = 1) \tag{35}$$

Here, the statistic S is expected to have a zero mean (under the null hypothesis), implying that the $CVaR_{t+1}^{\alpha}$ is under- and overestimating the tail risk for the next day to an exactly similar extent, if the VaR_{t+1}^{α} forecast generates a hit. A violation to the null hypothesis of a mean of zero showed a divergence from this assumption and thus structural under- or overestimation of the risk exposure in the tail of the return simulations. Since the present study is particularly interested in extreme risk and tail-risk estimation of coherent measurements in line with the axioms of Artzner et al. (1999), the analysis of the $CVaR_{t+1}^{\alpha}$ is of greater interest than the analysis of the VaR_{t+1}^{α}. Nonetheless, since the VaR_{t+1}^{α} is a widely used measurement in the banking industry for example, its importance for market participants is obvious.

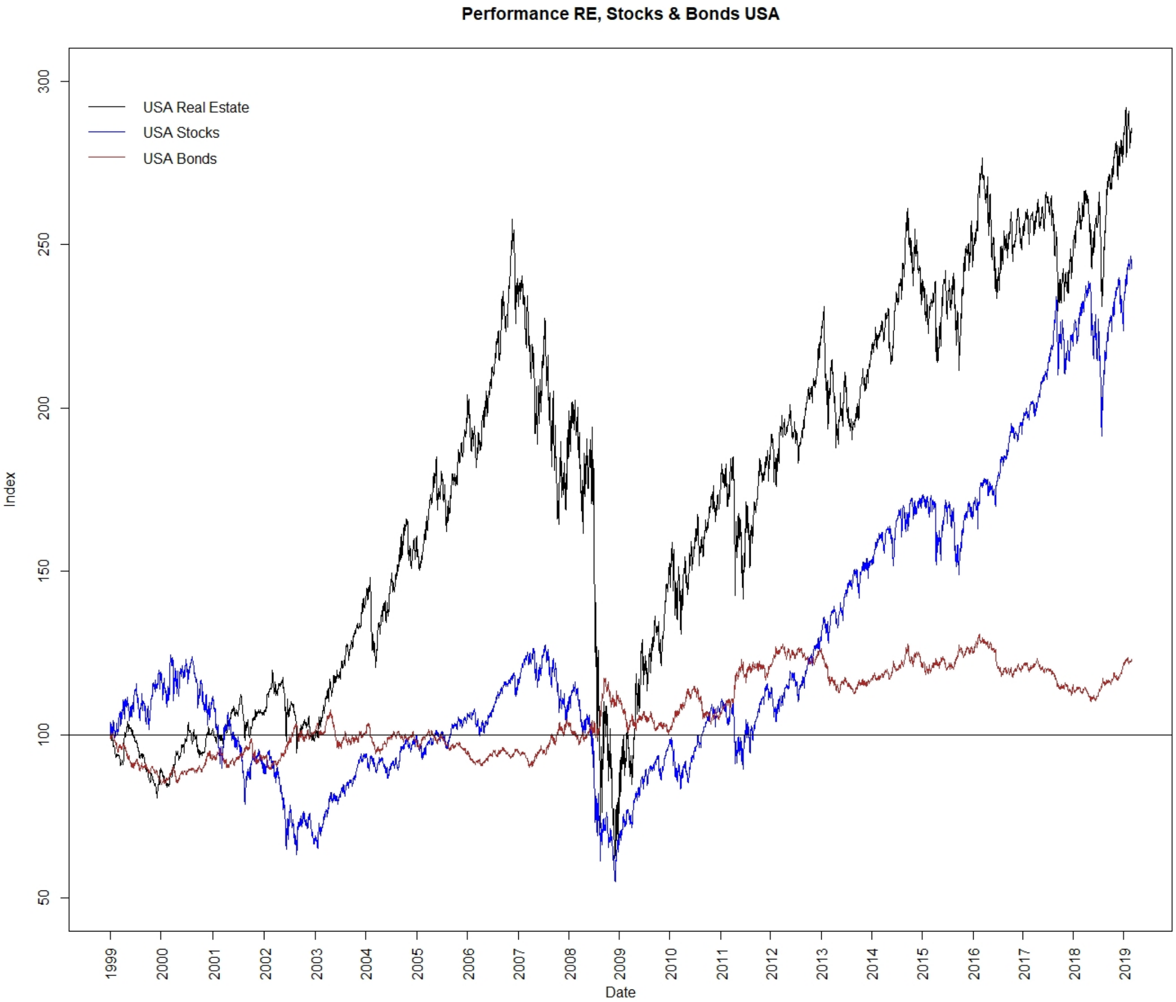
5.4 Data and descriptive statistics

The data covers daily log return observations for securitized real estate, equity and debt indices between January 4th 1999 and July 31st 2019. Due to data availability issues for some indices, we restricted our whole sample to start in January 1999. The inclusion of a trading day depends on the opening of all three asset class markets in the respective country. Thus, the number of observations can differ across countries due to differing public holidays or other specific distractions and market closure (such as 9/11 in the US). However, this heterogeneity does not affect the results, since the test statistics themselves are dependent on the number of observations.

The included markets are Australia, France, Germany, Japan, the UK and the US. These nations were chosen, since they represent the class of mature securitized real estate markets (e.g. as proposed by Liow, 2008). For this study however, Hong Kong and Singapore were excluded, because these countries do not provide a debt index of sufficient length. This sufficiency is defined as a time span which covers several prominent critical market phases (most importantly the GFC in 2008 and the Dot-com bubble in the late 1990s). This inclusion is important since the risk model is supposed to be tested and stressed through multiple periods of intense downturns. Cross-country dependencies were excluded for two reasons: Firstly, a clear market separation is supposed to be isolated to identify potential differences across national borders. Secondly, the idea to use data per country provokes simultaneous heavy downturns, since national markets are heavily integrated, causing additional stress on the risk forecasting.

As a first insight, the following figure shows the performance of our three main asset classes for the US market over the full sample period (see Figure 13):

Figure 13: Cumulated return series for real estate, stocks and bonds (US)



Notes: The graphic shows the cumulated returns of the real estate, stocks and bond series for the USA. Each series is starting at 100. Figures and graphics for the other countries in the sample are available upon request. Due to limited space we do not present those graphics here. Further descriptive statistics concerning these countries are showcased later on.

Source: Own presentation.

The variety of markets is introduced for two reasons. Firstly, a larger number of markets and thus dependencies of securitized real estate and the two other asset classes is intended to ensure robustness of the model. A market study on a single market appears to be insufficient to derive valid statements about global market behavior and in order to proof that our model may be eligible for more than just one specific market. Secondly, country specifics may be of interest, since the abovementioned crises are expected to be globally heterogeneous (e.g. especially extreme losses during the GFC in the US). For the securitized real estate, EPRA NAREIT All Equity indices are used. The equity data sets are the leading national indices, namely the ASX100 (Australia), CAC40 (France), DAX30 (Germany), Nikkei (Japan), FTSE100 (UK) and the S&P500 (US). The debt returns are from the countries' government bonds with ten-year maturity. For the outlined dataset constituents, the following table summarizes the descriptive statistics (see Table 23):

Table 23: Descriptive statistics

	AUS n = 5028	GER n = 5132	FRA n = 5134	JAP n = 4838	UK n= 5159	USA n = 5080
Panel A: Real Estate						
Mean	0.73	3.20	6.99	5.73	2.14	5.38
Std. Dev.	20.43	24.94	20.19	30.82	20.82	27.73
25th percentile	-75.24	-82.19	-76.66	-90.46	-73.78	-75.02
75th percentile	354.72	530.51	439.45	1100.99	349.26	426.55
Skewness	-0.70	0.05	-0.07	0.18	-0.57	-0.22
Kurtosis	29.22	8.70	4.38	4.84	10.35	22.25
JB	179309	16215	4111	4755	23323	104896
Q(16)	269	66	57	96	43	407
$Q^2(16)$	3651	3823	3894	3944	3892	11249
Panel B: Stocks						
Mean	12.66	4.48	1.68	2.32	1.24	4.48
Std. Dev.	25.03	23.36	22.64	24.05	18.53	19.14
25th percentile	-83.39	-81.69	-81.18	-83.84	-74.63	-70.88
75th percentile	744.81	557.95	532.42	696.63	338.85	330.53
Skewness	0.37	-0.06	-0.02	-0.36	-0.16	-0.25
Kurtosis	10.57	4.52	5.09	6.18	6.10	8.08
JB	23516	4385	5546	7811	8032	13901
Q(16)	269	66	57	96	43	407
$Q^2(16)$	3651	3823	3894	3944	3892	11249
Panel C: Bonds						
Mean	1.40	2.45	2.53	1.81	1.91	1.01
Std. Dev.	7.71	5.54	5.63	3.96	6.19	7.50
25th percentile	-49.78	-37.72	-38.03	-23.09	-42.73	-50.29
75th percentile	112.71	75.94	74.27	38.14	85.04	109.67
Skewness	-0.14	-0.21	-0.23	-0.56	0.04	-0.05
Kurtosis	2.95	1.75	2.59	6.90	1.86	2.52
JB	1843	695	1485	9854	746	1348
Q(16)	59	63	70	80	58	60
$Q^2(16)$	772	677	1465	3786	575	1040

Notes: The table presents descriptive statistics of the three asset return series for each of the six countries in our sample. The figures for mean, standard deviation, the 25th as well as the 75th percentile are annualized under the assumption of 252 (trading) days per year and reported in percent. For Jarque-Bera, Q(16) and $Q^2(16)$, we state the individual test statistic.

Source: Own presentation.

From the statistical moments of the distributions, various insights can be derived. Firstly, the mean of all return series are virtually zero, which is in line with expectations, since log returns are used. The dispersion of the data is highest for four of the real estate time series (except for Australia and France). Skewness is mainly close to zero and positive for each return series, showing skew towards the right. Hence, the observed skew justifies the application of the skewed-t errors for the univariate models. The large kurtosis of all returns indicates leptokurtic distributions. In addition to the statements about return series volatility for securitized real estate, the minima reveal the largest downturns for the specified asset class (except for France). In the context of risk management and metric forecasting, these extreme values are of particular interest, since these returns are the most likely observations to cause violations of the price risk forecast of the VaR^{α} and the $CVaR^{\alpha}$ in comparison to the real return.

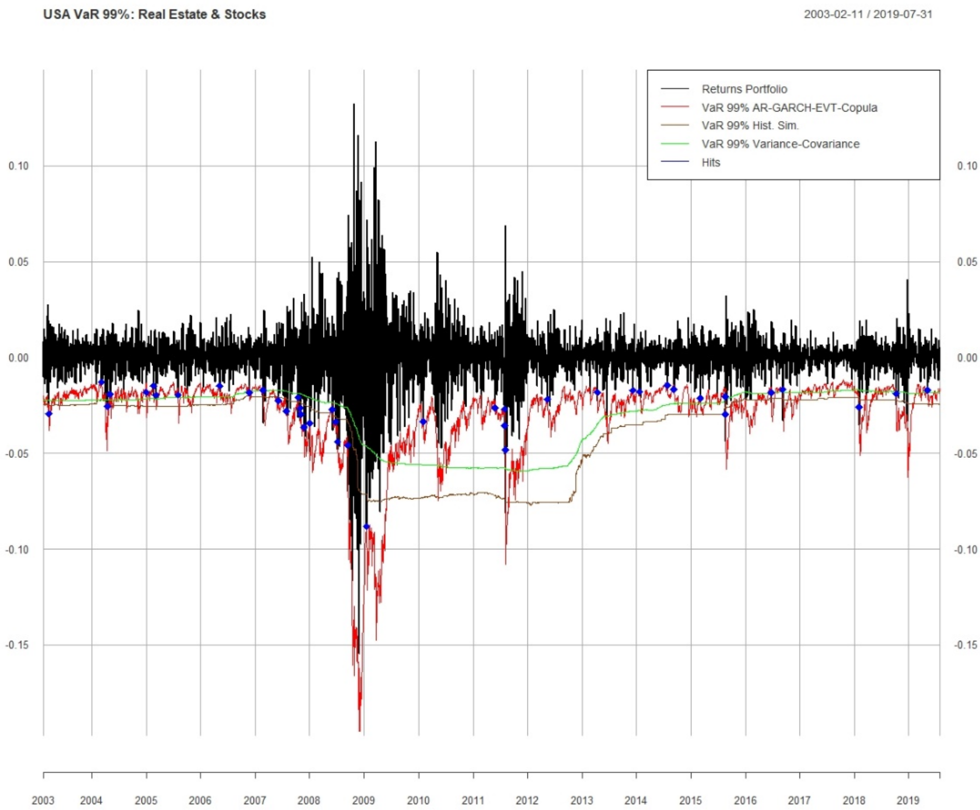
The descriptive statistics also reveal evidence of other statistical issues mentioned in the literature review. These indicate a compelling need for the application of the AR-GARCH-EVT-Copula approach. This applies especially to the securitized real estate data. Additionally, the Jarque-Bera tests yield very strong empirical evidence of the violation of normality for each time series of the dataset. In addition, serial correlation can be detected due to the findings of the Q(16) and $Q^2(16)$ statistics. Thus, the application of statistical procedures to account for these issues is needed to ensure unbiased univariate and multivariate modelling.

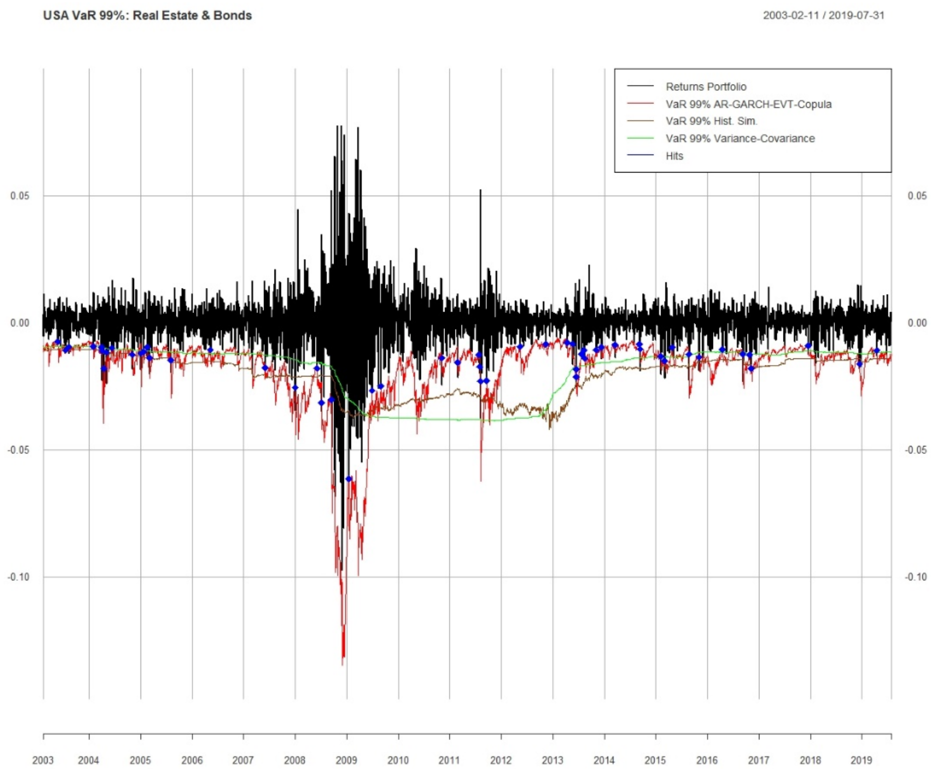
5.5 Empirical results

The empirical analysis covers the results of the back testing for the AR-GARCH-EVT-Copula and the two benchmark methodologies, namely variance-covariance and historical simulation for the specified return series.[24] For each approach, risk forecasts for the equally weighted portfolio are calculated and compared to the actual portfolio return. Graphically, the figures below display the $VaR^{0.99}$ from the AR-GARCH-EVT-Copula model as well as both benchmark methodologies for both portfolios from the US (see Figure 14):

[24] Implementing the AR-GARCH-EVT-Copula model leads to a load of typical estimates. Since the estimates change over time due to the usage of rolling windows, those estimates can only be illustrated in figures. These figures for AR-GARCH estimates, scale and shape as well as copula parameters are available upon request.

Figure 14: VaR ($\alpha = 0.99$) estimates for Real Estate – Stocks & Real Estate - Bonds portfolio (US)





Source: Own presentation.

From the graphical representation of the observed returns (black lines) and the risk forecasts, the primary difference between the benchmark models and the AR-GARCH-EVT-Copula model is the relative responsiveness of the latter approach to differing levels of market volatility, and especially extreme losses (as displayed by the red lines). In comparison, the benchmark methods do not provide this flexibility and react to periods of increasing volatility and heavy downturns (e.g. the GFC) and also to decreased volatility too reluctantly and late (e.g. the brown and green graphs both respond in early 2013 by indicating significantly lower risk forecasts). This finding applies to both portfolio scenarios alike as well as across all countries in our sample.

One explanation may be the increased correlation between asset classes especially in downturn markets (Case et al., 2012), which can cause extreme simultaneous asset losses, contradicting heavily with the assumption of constant correlation of the benchmark methodologies. Accordingly, refitting the dependence structure appears to be a key element of appropriate risk metric forecasting, due to breakdowns in correlation patterns during increased volatility.

Beside optical inspection, numerical measures provide deeper insight into the model accuracy. By back-testing the methodologies through the data sample, the absolute and relative number of hits, the corresponding Bernoulli as well as the Kupiec statistics are displayed for the $VaR_{t+1}^{\propto}$ (see Table 24). Additionally, for the $CVaR_{t+1}^{\propto}$, the zero mean test results are shown on Table 24.[25]

Table 24: Empirical results for VaR forecasts

				VaR				
Country	Portfolio	Risk Metric	Model	Hits	Relative Hits	p-value Bernoulli	p-value Kupiec	p-value Christoffersen
Australia (n = 4026)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	94	2.33	0.00	0.00	0.00
			Hist. Sim.	59	1.47	0.53	0.55	0.09
			AR-GARCH-EVT-Copula	42	1.04	75.12	78.43	20.77
		$V\ R_{t+1}^{0.05}$	Variance-Covariance	211	5.24	46.96	48.63	1.38
			Hist. Sim.	216	5.37	29.42	29.32	0.83
			AR-GARCH-EVT-Copula	225	5.59	8.91	9.23	23.88
	Real Estate - Bonds	$VaR_{t+1}^{0.01}$	Variance-Covariance	93	2.31	0.00	0.00	0.00
			Hist. Sim.	59	1.47	0.53	0.55	0.00
			AR-GARCH-EVT-Copula	55	1.37	2.60	2.70	1.17
		$VaR_{t+1}^{0.05}$	Variance-Covariance	209	5.19	56.29	57.99	0.00
			Hist. Sim.	236	5.86	1.39	1.45	0.00
			AR-GARCH-EVT-Copula	226	5.61	7.64	7.96	0.86
France (n = 4134)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	84	2.03	0.00	0.00	0.00
			Hist. Sim.	44	1.06	63.89	67.84	0.04
			AR-GARCH-EVT-Copula	49	1.19	23.98	24.34	3.66
		$VaR_{t+1}^{0.05}$	Variance-Covariance	185	4.48	12.49	11.68	0.00
			Hist. Sim.	221	5.35	30.06	30.92	0.00
			AR-GARCH-EVT-Copula	186	4.50	15.32	13.50	0.12

[25] The results for the portfolios containing stocks and bonds are available upon request.

	Real Estate - Bonds	$VaR_{t+1}^{0.01}$	Variance-Covariance	91	2.20	0.00	0.00	0.00
			Hist. Sim.	44	1.06	63.90	68.07	22.07
			AR-GARCH-EVT-Copula	46	1.11	43.46	47.43	64.23
		$VaR_{t+1}^{0.05}$	Variance-Covariance	231	5.59	8.66	8.85	0.00
			Hist. Sim.	202	4.89	77.53	73.64	0.00
			AR-GARCH-EVT-Copula	221	5.35	30.08	31.27	0.10
Germany (n= 4132)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	83	2.01	0.00	0.00	0.00
			Hist. Sim.	42	1.02	87.57	91.56	0.03
			AR-GARCH-EVT-Copula	35	0.85	38.88	31.02	44.31
		$VaR_{t+1}^{0.05}$	Variance-Covariance	185	4.48	12.49	11.68	0.00
			Hist. Sim.	196	4.74	47.53	44.55	0.00
			AR-GARCH-EVT-Copula	197	4.77	52.05	49.00	9.13
	Real Estate - Bonds	$Va_{t+1}^{0.01}$	Variance-Covariance	84	2.03	0.00	0.00	0.00
			Hist. Sim.	44	1.06	63.89	67.84	0.04
			AR-GARCH-EVT-Copula	49	1.19	23.98	24.34	3.66
		$VaR_{t+1}^{0.05}$	Variance-Covariance	185	4.48	12.49	11.68	0.00
			Hist. Sim.	221	5.35	30.06	30.92	0.00
			AR-GARCH-EVT-Copula	186	4.50	15.32	13.50	0.12
Japan (n = 3838)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	70	1.82	0.00	0.00	0.00
			Hist. Sim.	49	1.28	8.81	9.89	2.22
			AR-GARCH-EVT-Copula	39	1.02	87.11	92.14	18.15
		$VaR_{t+1}^{0.05}$	Variance-Covariance	161	4.19	2.16	1.85	0.00
			Hist. Sim.	169	4.40	9.55	8.30	0.00
			AR-GARCH-EVT-Copula	187	4.87	73.90	71.28	76.20
	Real Estate - Bonds	$VaR_{t+1}^{0.01}$	Variance-Covariance	50	1.30	6.20	7.19	0.31
			Hist. Sim.	31	0.81	25.59	21.49	24.11
			AR-GARCH-EVT-Copula	33	0.86	41.78	37.03	6.84
		$VaR_{t+1}^{0.05}$	Variance-Covariance	141	3.67	0.01	0.01	0.00
			Hist. Sim.	134	3.49	0.00	0.00	0.00
			AR-GARCH-EVT-Copula	172	4.48	14.86	13.29	0.70
United Kingdom (n = 4159)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	92	2.21	0.00	0.00	0.00
			Hist. Sim.	51	1.23	13.87	15.67	13.65
			AR-GARCH-EVT-Copula	43	1.03	81.48	82.70	21.58
		$VaR_{t+1}^{0.05}$	Variance-Covariance	204	4.91	80.34	77.80	0.00
			Hist. Sim.	211	5.07	83.09	82.86	0.00
			AR-GARCH-EVT-Copula	203	4.88	74.89	72.37	73.82
	Real Estate - Bonds	$VaR_{t+1}^{0.01}$	Variance-Covariance	105	2.52	0.00	0.00	0.00
			Hist. Sim.	62	1.49	0.29	0.30	0.01
			AR-GARCH-EVT-Copula	54	1.30	6.07	6.45	16.98
		$VaR_{t+1}^{0.05}$	Variance-Covariance	227	5.46	17.63	18.14	0.00
			Hist. Sim.	228	5.48	15.47	15.98	0.00
			AR-GARCH-EVT-Copula	223	5.36	28.57	28.96	0.54
USA (n = 4080)	Real Estate - Stocks	$VaR_{t+1}^{0.01}$	Variance-Covariance	105	2.57	0.00	0.00	0.00
			Hist. Sim.	60	1.47	0.44	0.48	0.01
			AR-GARCH-EVT-Copula	42	1.03	81.33	85.09	74.36
		$VaR_{t+1}^{0.05}$	Variance-Covariance	204	5.00	100.00	100.00	0.00
			Hist. Sim.	221	5.42	22.19	22.80	0.00

		AR-GARCH-EVT-Copula	206	5.05	88.57	88.59	3.87
Real Estate - Bonds	$VaR_{t+1}^{0.01}$	Variance-Covariance	114	2.79	0.00	0.00	0.00
		Hist. Sim.	68	1.67	0.01	0.01	0.00
		AR-GARCH-EVT-Copula	56	1.37	2.20	2.36	3.80
	$VaR_{t+1}^{0.05}$	Variance-Covariance	264	6.47	0.00	0.00	0.00
		Hist. Sim.	265	6.50	0.00	0.00	0.00
		AR-GARCH-EVT-Copula	249	6.10	0.18	0.18	0.00

Notes: The number of observations (n) equals to the number of total observations for each country less the burn-in sample of 1000 observations. Relative hits are calculated as the number of actual hits divided by total observations. Relative hits as well as p-values are given in percent. Null hypotheses for Bernoulli, Kupiec and Christoffersen tests are described in detail in the methodology section (formulas 11, 12 & 13). In short, for the Bernoulli test, the null hypothesis is that the results do not differ significantly from the expected number of hits. The null hypothesis for the Kupiec test states that the observed failure rate is equal to the failure rate suggested by the confidence interval. Finally, the null hypothesis of the Christoffersen test describes the correct number of exceedances and the independence of failures. Further results, back-tests and graphics for all Stocks-Bonds pairs are available upon request.

Source: Own presentation.

For the VaR_{t+1}^{α}, the results provide numerical proof of improvements in the violation-based figures at both levels of significance. The absolute as well as the relative number of hits provide some initial but rather sparse insight into the quality of the proposed model. For example, for the $VaR_{t+1}^{0.01}$, the expected number of relative hits should be exactly one percent, as it is the case for the Australian real estate & stocks portfolio. Additionally, one would rather underestimate the number of violations than overestimate it. Tendencies to underestimate the number of violations do not involve such grave consequences for portfolio holders as overestimation. For the $VaR_{t+1}^{0.05}$, the p-values suggest partial missing improvements of the AR-GARCH-EVT-Copula model, for example for the Real Estate & Bond portfolio in Japan. However, the majority of the results confirm the superiority of the model in comparison to the benchmarks. Even more significant confirmation can be found for the $VaR_{t+1}^{0.01}$. Here, all countries and portfolios show improved violation-based figures for the Bernoulli and Kupiec tests. Thus, it can be stated that the AR-GARCH-EVT-Copula model is especially feasible for tail-risk estimation, since the model outperforms the benchmark more clearly with an increased level of confidence.

With regard to the Christoffersen test and thus the temporal dimension of the model hits, the p-values show temporal independence of the AR-GARCH-EVT-Copula model. For $VaR_{t+1}^{0.01}$, the unanimous approval of independence for the AR-GARCH-EVT-Copula model is supported, whereas the benchmark models fail to generate hits without temporal dependence at the one percent level. The results of the $VaR_{t+1}^{0.05}$, however, contain some p-values which indicate temporal dependence, especially for the real estate & bond portfolios (e.g. in the US & the UK). It becomes apparent that the benchmark models produce hits with a clear timely pattern.

In sum, the violation-based and the independence tests yield similar results, in favour of the AR-GARCH-EVT-Copula model. Turning to the $CVaR_{t+1}^{\propto}$, the following table summarizes the back-testing and the especially the zero mean test results (see Table 25):

Table 25: Empirical results for CVaR forecasts

			CVaR			
				Hits	Relative Hits	p-Value Zero Mean Test
Australia (n = 4026)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	66	1.64	0.00
			Hist. Sim.	19	0.47	57.66
			AR-GARCH-EVT-Copula	11	0.27	96.75
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	133	3.30	0.00
			Hist. Sim.	89	2.21	1.35
			AR-GARCH-EVT-Copula	45	1.12	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	67	1.66	0.00
			Hist. Sim.	21	0.52	43.35
			AR-GARCH-EVT-Copula	13	0.32	99.74
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	136	3.38	0.00
			Hist. Sim.	91	2.26	7.35
			AR-GARCH-EVT-Copula	63	1.56	100.00
France (n = 4134)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	55	1.33	0.00
			Hist. Sim.	20	0.48	15.62
			AR-GARCH-EVT-Copula	14	0.34	82.49
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	119	2.88	0.00
			Hist. Sim.	73	1.77	11.49
			AR-GARCH-EVT-Copula	62	1.50	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	57	1.38	0.00
			Hist. Sim.	23	0.56	25.46
			AR-GARCH-EVT-Copula	16	0.39	94.34
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	139	3.36	0.00
			Hist. Sim.	78	1.89	64.26
			AR-GARCH-EVT-Copula	64	1.55	100.00
Germany (n = 4132)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	56	1.36	0.00
			Hist. Sim.	20	0.48	7.64
			AR-GARCH-EVT-Copula	4	0.10	100.00
		$VaR_{t+1}^{0.05}$	Variance-Covariance	113	2.73	0.00
			Hist. Sim.	81	1.96	11.22
			AR-GARCH-EVT-Copula	64	1.55	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	64	1.55	0.00
			Hist. Sim.	20	0.48	27.40
			AR-GARCH-EVT-Copula	12	0.29	99.99
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	114	2.76	0.00
			Hist. Sim.	76	1.84	79.12
			AR-GARCH-EVT-Copula	72	1.74	100.00
Japan (n = 3838)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	54	1.41	0.00
			Hist. Sim.	20	0.52	19.53

			AR-GARCH-EVT-Copula	16	0.42	68.49
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	88	2.29	0.00
			Hist. Sim.	73	1.90	4.07
			AR-GARCH-EVT-Copula	52	1.35	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	71	0.81	0.00
			Hist. Sim.	26	0.36	18.39
			AR-GARCH-EVT-Copula	15	0.34	85.75
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	146	1.90	0.00
			Hist. Sim.	94	1.07	3.77
			AR-GARCH-EVT-Copula	52	1.41	100.00
United Kingdom (n = 4159)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	66	1.59	0.00
			Hist. Sim.	27	0.65	2.53
			AR-GARCH-EVT-Copula	13	0.31	58.22
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	122	2.93	0.00
			Hist. Sim.	84	2.02	3.01
			AR-GARCH-EVT-Copula	51	1.23	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	71	1.71	0.00
			Hist. Sim.	26	0.63	18.39
			AR-GARCH-EVT-Copula	15	0.36	85.75
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	146	3.51	0.00
			Hist. Sim.	94	2.26	3.77
			AR-GARCH-EVT-Copula	52	1.25	100.00
USA (n = 4080)	Real Estate - Stocks	$CVaR_{t+1}^{0.01}$	Variance-Covariance	76	1.86	0.00
			Hist. Sim.	37	0.91	0.57
			AR-GARCH-EVT-Copula	13	0.32	95.62
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	128	3.14	0.00
			Hist. Sim.	96	2.35	3.72
			AR-GARCH-EVT-Copula	63	1.54	100.00
	Real Estate - Bonds	$CVaR_{t+1}^{0.01}$	Variance-Covariance	82	2.01	0.00
			Hist. Sim.	27	0.66	22.31
			AR-GARCH-EVT-Copula	23	0.56	59.27
		$CVaR_{t+1}^{0.05}$	Variance-Covariance	158	3.87	0.00
			Hist. Sim.	93	2.28	14.74
			AR-GARCH-EVT-Copula	71	1.74	100.00

Notes: The number of observations (n) equals the number of total observations for each country less the burn-in sample of 1000 observations. Relative hits are calculated as the number of actual hits divided by total observations. Relative hits as well as p-values are given in percent. As a reminder, the null hypothesis for the zero mean test is that the excess conditional shortfall, is i.i.d. and has zero mean. See formula 14 and methodology section for detailed information. Further results, back-tests and graphics for all Stocks-Bonds pairs are available upon request.

Source: Own presentation.

The results for the $CVaR_{t+1}^{\propto}$ indicate at both levels a clear superiority of the AR-GARCH-EVT-Copula approach in comparison to the benchmarks. The variance-covariance method clearly produces hit sequences, which do not exhibit a mean of zero. The historical simulation approach shows a superior hit sequence compared to the variance-covariance method. Nonetheless, the AR-GARCH-EVT-

Copula method shows the highest p-values across all markets and portfolios. Thus, the $CVaR_{t+1}^{\propto}$ results suggest outperformance of the benchmark at both levels of significance. The results can be interpreted as confirmation for structural under- and overestimation of the $CVaR_{t+1}^{\propto}$, if $VaR_{t+1}^{\propto}$ is violated. This does not apply to the variance-covariance method, and only partially to the historical simulation. Taking the graphical inspection into account, especially the heavy underestimation of losses during the GFC may cause these results for the benchmarks.

In sum, the results provide empirical evidence, both graphically and numerically, of an improved risk measurement of the AR-GARCH-EVT-Copula in comparison to the benchmark methodologies. In particular, the re-estimation of dependence patterns appears to be a key feature for correctly modelling its time-variance. Since the results also show greater improvements for risk measurements of the tail (e.g. the larger confirmation of the $VaR_{t+1}^{0.99}$ than the $VaR_{t+1}^{0.95}$), the dependence patterns of the analysed asset classes may also reveal a need to model non-linear relationships in contrast to the strictly linear correlation measurement. This applies especially to critical market phases, since the graphical inspection revealed heavy underestimation of the risk exposure in these periods (e.g. during the GFC). Since the $CVaR_{t+1}^{\alpha}$ represents a coherent risk measurement in accordance with Artzner et al. (1999), as proposed by Rockafellar & Uryasev (2000), the results imply the feasibility of the AR-GARCH-EVT-Copula model especially for the named figure.

Based upon the empirical results of the back-testing, questions arise regarding the underlying univariate and multivariate models. Since varying models are used for each rolling window of the AR-GARCH-EVT-Copula approach, a deeper look into the results for the autoregressive and dependence models for each portfolio may provide additional information. Therefore, Table 26 displays the results of the goodness of fit for the autoregressive models for each time series. More precisely, Table 26 reports the discrete distribution for the highest fit of each autoregressive order across the respective data series for the rolling windows (see Table 26):

Table 26: Results of the autoregressive modelling

Autoregressive Order	US Real Estate	UK Real Estate	DE Real Estate	FR Real Estate	AUS Real Estate	JP Real Estate	Sum
0	977	638	312	998	753	100	3778
1	999	1053	885	287	67	578	3869
2	244	401	387	506	265	268	2071
3	110	333	272	686	934	614	2949
4	475	628	594	416	390	868	3371
5	1275	1106	1682	1241	1617	1411	8332
	US Stocks	UK Stocks	DE Stocks	FR Stocks	AUS Stocks	JP Stocks	Sum
0	0	268	749	244	965	1065	3291

1	624	454	536	318	216	738	2886
2	461	298	108	352	143	296	1658
3	126	791	131	563	253	212	2076
4	433	920	142	359	1359	783	3996
5	2436	1428	2466	2298	1090	745	10463
	US Bonds	UK Bonds	DE Bonds	FR Bonds	AUS Bonds	JP Bonds	Sum
0	811	674	451	1211	458	607	4212
1	419	406	433	303	600	212	2373
2	838	472	1021	715	1379	131	4556
3	275	687	266	406	554	1116	3304
4	407	417	653	660	447	583	3167
5	1330	1503	1308	839	588	1190	6758

Notes: *The table displays the number of occurrences of the highest fit for the respective autoregressive order by asset class and country as well as the sum across the row.*

Source: Own presentation.

Firstly, the univariate results reveal the highest percentage of best fitting models for the autoregressive order of five (34.95% of the overall number of windows across all asset classes). The distribution across the remaining five orders yield homogenous results between 11.33% – 15.43% of the overall number of windows across all time series.

Considering the cross-section of asset classes, a pattern can be observed for real estate and stocks. Firstly, the goodness of fit for the lower orders yield percentages in double figures, decreasing through the second and third order, regaining fit in the lags four and five.[26] For bonds in comparison, the autoregressive models in the middle of the tested orders are more accurate and reveal a significantly higher percentage of fits for order two. Thus, with regard to the autoregressive character of the data, bonds are the asset class, which behave more balanced across the autoregressive orders than its peers in the sample. For securitized real estate and stocks, 34.19%, or 42.93% respectively, of the overall windows are modelled best by an autoregressive model of order five. In comparison, only 27.73% of the bond windows are showing the highest fit for the longest autoregressive order. Since public equity positions such as securitized real estate and stocks are known for their long-lasting and heavy serial autocorrelation, the univariate results are in line with expectations based on the literature review above.

Within the asset classes, the results also reveal a certain extent of heterogeneity across the markets. For securitized real estate, Germany and Japan show extremely low number of occurrences for order zero. In contrast, the time series for Germany also displays the highest number for the longest order. Another notable unusualness within the securitized real estate data is the extremely low number of order one models for the Australian time series. In addition to the low number of order zero models,

[26] With an interesting outlier of US stocks, with a total number of zero times for the highest fit of order zero.

Australia appears to be a market with more long-lasting autoregressive effects. The same applies to Japan. The US and the UK on the other hand are markets with more occurrences (1,976 and 1,691) of short autoregressive effects (zero and one).

For the other asset classes, a surprising finding is the missing occurrence for the zero. Thus, the US stock time series entails autoregressive effects for every window. In fact, the data for the US stocks time series is heavily long-lasting autoregressive (2,436 observations for the highest order). For the bond data, the results reveal the highest occurrences for the middle orders (especially two and three), as outlined above.

Nonetheless, from a methodological point of view, an extension to even higher autoregressive orders could be thinkable for further model improvements especially for securitized real estate and stocks. With regard to the implications for the price risk forecasting model of interest, the general necessity to allow for individual order selection based on the respective goodness of fit can be extracted from the results, since the asset classes and markets of the study show largely differing results and thus individual specifics.

Based on these univariate findings, the multivariate results are assessed. In particular, the question is, what types of copulae are providing the highest fit overall and for which specific portfolios or markets. From the chosen type of copula alone, insights about the symmetry of the co-movements of the portfolio constituents can be derived. Therefore, table 27 summarizes the discrete distribution of the copulae with the highest fit among the tested ones for each rolling window across all asset classes and countries (see Table 27):

Table 27: Empirical results for the copulae estimation

Copula type	Australia		France		Germany		Japan		United Kingdom		United States		Sum		
	RE-Stocks	RE-Bonds	RE-Stocks	RE-Bonds	RE-Stocks	RE-Bonds	RE-Stocks	RE-Bonds	RE-Stocks	RE-Bonds	RE-Stocks	RE-Bonds	all	RE-Stocks	RE-Bonds
Gaussian	2	158	219	70	336	0	364	140	66	128	0	2240	3723	987	2736
Student t	2770	611	1904	2075	2558	2131	2218	1866	2406	2510	3983	17	25049	15839	9210
Clayton	0	0	0	98	40	0	0	0	0	00	0	0	138	40	98
Gumbel	0	242	0	0	0	0	0	0	0	0	0	0	242	0	242
Frank	45	31	0	16	0	0	0	1053	0	84	0	0	1229	45	1184
BB1	832	0	107	0	210	0	437	0	4	0	40	0	1630	1630	0
BB7	0	149	249	0	0	0	0	0	0	0	0	0	398	249	149
survival Clayton	0	291	0	0	0	0	0	0	0	0	0	0	291	0	291
survival Gumbel	16	0	388	0	376	0	0	0	842	0	0	0	1622	1622	0
survival Joe	0	182	0	0	0	6	0	0	0	0	0	281	469	0	469
survival BB1	117	0	917	0	442	0	819	0	841	0	57	0	3193	3193	0
survival BB7	0	37	350	0	9	0	0	0	0	0	0	0	396	359	37
survival BB8	244	0	0	0	85	0	0	0	0	0	0	180	509	329	180
rotated Clayton (90 degrees)	0	0	0	459	0	0	0	52	0	83	0	0	594	0	594
rotated Gumbel (90 degrees)	0	494	0	127	0	96	0	8	0	246	0	1062	2033	0	2033
rotated Joe (90 degrees)	0	239	0	0	0	2	0	0	0	0	0	146	387	0	387
rotated BB1 (90 degrees)	0	0	0	417	0	443	0	271	0	0	0	122	1253	0	1253
rotated BB7 (90 degrees)	0	0	0	176	0	54	0	0	0	0	0	32	262	0	262
rotated BB8 (90 degrees)	0	1449	0	1	0	150	0	90	0	174	0	0	1864	0	1864
rotated Clayton (270 degrees)	0	1	0	284	0	620	0	138	0	34	0	0	1077	0	1077
rotated Gumbel (270 degrees)	0	1	0	67	0	0	0	153	0	116	0	0	337	0	337
rotated Joe (270 degrees)	0	141	0	11	0	0	0	0	0	0	0	0	152	0	152
rotated BB1 (270 degrees)	0	0	0	52	0	543	0	0	0	761	0	0	1356	0	1356
rotated BB7 (270 degrees)	0	0	0	281	0	87	0	0	0	23	0	0	391	0	391
rotated BB8 (270 degrees)	0	0	0	0	0	0	0	67	0	0	0	0	67	0	67

Notes: *The table displays the number of occurrences of the highest fit for each of the tested copula. Not displayed are copulae, which failed to reach a single highest fit.*

The major finding of the multivariate modelling is the clear dominance of the Student-t-Copula. Out of the total number of windows, more than 51.53% of the dependence models reveal the highest goodness of fit for the named copula, implying a symmetric but existing tail dependence. This finding, however, is largely driven by the dependence of securitized real estate and stocks, since 63.23% of the Student-t-Copula models apply the named portfolio constituents. This finding is in line with the expectations based on the literature review, because previous studies have repeatedly shown this simultaneous market behaviour of securitized real estate and stocks.

Interestingly, out of the entire data set the second-best fitting copula family is the Gaussian. 7.71% of the relationships are modelled by a Gaussian copula, which is contradicting the assumption of non-normality of the joint marginal. This finding, however, is largely impacted by the results of the US real estate – bond portfolio, on its own already accounting for 2,240 out of the 3,723 total windows, which are modelled by the Gaussian copula. This finding can be interpreted as a sign for no tail dependence of the specified portfolio constituents. Other markets do not support the application of the Gaussian copula, which reduces the finding to a market specific phenomenon.

Thirdly, the survival BB1 copula models 3,191 dependencies out of the sample. The named copula type also shows an entirely skewed distribution across the portfolio constituents, since only real estate – stocks portfolios are displayed. This 180-degree rotated copula, with lower tail dependence but higher variance in the empirical density in the named tail reveals the potential for simultaneous but also less dense realizations in the tail. Thus, portfolios tend to show higher variance in the tail observations, but still existing asymmetric dependence.

Furthermore, the rotated copulae (both, 90 and 270°) are only used by securitized real estate and bonds. This finding is highly important for securitized real investors, who seek multi-asset diversification and correct portfolio modelling. Generally, these rotated copulae symbolize opposing price movements, because they are used to model data, which explicitly shows positive (negative) returns of one asset, when the other asset moves in the opposite direction. Thus, this finding implies the strict necessity to apply the specified copulae, when securitized real estate and bond positions are gathered in a portfolio to fully capture the nature of the data. This finding is especially of interest from a strategic risk management point of view, because these occurrences imply the possibility to hedge price risk movements of the named asset classes. Whereas this finding is not new to the real estate literature, the empirical dependence modelling by using rotated copulae has not been extensively studied.

5.6 Conclusion

The present study contributes to the existing body of real estate literature by extending the stream of publications on copula dependence modelling with the empirical study, not only of the parameters of the dependence structures and fit assessment, but by the actual application of nonlinear dependence modelling to price risk metric forecasting. Therefore, the dependence modelling is extended and enriched by univariate modelling and the Monte Carlo simulation, based on copula dependence using the so-called AR-GARCH-EVT-Copula approach. After describing the conceptual construction of the risk model, the empirical study reveals improvements in the specified methodology across different risk metrics and levels of significance.

The study also reveals that the VaR^{α} based on AR-GARCH-EVT-Copula provides better one-day-ahead estimates, compared to the traditional $VaR^{\alpha}/CVaR^{\alpha}$ estimation methods (variance-covariance and historical simulation). The results of simple violation ratios and additional test statistics like Kupiec, Christoffersen and zero mean for our model at different significance levels, were within the range of a superior estimation model. A detailed decomposition of the model revealed the necessity for univariate modelling of high autoregressive orders. Additionally, the multivariate analysis showed the predominant symmetric and negative tail dependence mainly for securitized real estate and stocks, but also towards bonds. In addition, the results of the multivariate modelling of securitized real estate and bonds showed evidence to incorporate rotated copulae at both levels of rotation to fully capture the dependence correctly. A limitation on classic elliptical and Archimedean copulae does not provide the necessary range of dependence structures.

The practical implications are the viable implementation of the presented approach and the replacement of variance-covariance or historical simulation methods for the specified asset classes. Especially in periods of extreme volatility and accordingly heavy negative daily returns, investors can benefit from improved risk metric forecasts in comparison to classic models. $VaR^{\alpha}$and $CVaR^{\alpha}$have also been widely used as risk measures by many financial institutions and regulators, such as the Basel Committee on Banking Supervision. Hence, our results also provide further insight into the correct approach of estimating these risk measures for those market participants.

Future research may also incorporate cross-country dependencies, which were not studied in this article. This could be especially useful for investors who diversify their portfolios across geographical borders. An extensive focus on securitized real estate could be thinkable, by analyzing portfolios of indirect property investment indices from different countries. Furthermore, an extension towards different types of equity securities could be beneficial, such as small or medium cap or debt positions like high or low yield. Additionally, it should be mentioned that only mature securitized real estate markets were analyzed in the present study. An extension to less mature markets can be useful so as to compare the feasibility of the model between mature and immature markets, although potential data limitations may occur. Potentially interesting studies would include those on the underlying copulae and a comparative study of them. Since the present approach uses switching copulae for each window, the fixation of a copula type and subsequent simulation out of each copula across the entire sample may be beneficial in detecting differences across varying dependence models. In this context, the investigation of a true time-varying parameter model with Bayesian updates could be of interest. Lastly, the option to investigate the ability to use the AR-GARCH-EVT-Copula approach as portfolio optimization tool, as applied for example by Chakkalakal et al. (2018) could be subject to future research.

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5.8 Appendix

Table 28: List of applied copulae

Bivariate Copula family				
One parameter	**Two parameters**	**90°-rotated**	**180°-rotated**	**270°-rotated**
Gaussian	Clayton-Gumbel (BB1)	Clayton	Clayton	Clayton
Student-t	Joe-Gumbel (BB6)	Gumbel	Joe	Gumbel
Clayton	Joe-Clayton (BB7)	Joe	Joe-Gumbel (BB6)	Joe
Gumbel	Joe-Frank (BB8)	Clayton-Gumbel (BB1)	Joe-Frank (BB8)	Clayton-Gumbel (BB1)
Frank		Joe-Gumbel (BB6)		Joe-Gumbel (BB6)
Joe		Joe-Clayton (BB7)		Joe-Clayton (BB7)
		Joe-Frank (BB8)		Joe-Frank (BB8)

Source: Own presentation.

6 Conclusion

6.1 Conclusion

The present thesis aims to explore selected aspects concerning the risk management of direct as well as indirect real estate positions in times of prevailing low interest and legal tightening. To improve the understanding of real estate risk management, chapter 1 outlines the motivation and the current relevant issues in the scientific discussion of the academic discipline. Chapters 2 to 5 cover the articles of the cumulative thesis. The articles are clearly separated along the securitizing function of indirect investment vehicles since the first two articles analyze aspects of the risk management of direct real estate markets, and the latter two in capital markets.

Chapter 2 presents a paper that aims to parameterize the impact of domestic or global political uncertainty on total returns of office properties. The empirical analysis applies a classic OLS approach to model total returns as a function of macroeconomic as well as real-estate-related controls. Additionally, proxies for domestic and global economic political uncertainty are introduced. The primary hypothesis states a negative relationship between domestic economic political uncertainty and office returns. The empirical study does not provide any evidence to falsify the hypothesis because the coefficients of the proxy are c.p., on average statistically significant and positive for different lags across all specifications. The second hypothesis outlines a potential negative effect of the global economic uncertainty on total returns due to macroeconomic spillover effects. In fact, the fourth lag of the global economic political uncertainty proxy shows, c.p. on average a statistically significant positive impact on the total returns throughout all specifications. Thus, the study provides empirical evidence for rejecting the second hypothesis. In sum, the empirical investigation contributes to the existing literature by adding the economic political environment as a significant part of the non-fundamental drivers of real estate market performance and thus a potential risk factor for investors.

Chapter 3 analyzes the impact of the *relative* yield or risk premia attractiveness of a direct real estate market compared to surrounding destinations on inflowing foreign capital. Both linear and non-linear models are applied, isolating on average, c.p., a statistically significant and timely lagged positive influence of the risk premia on cross-border transaction volumes. The relationship is statistically insignificant for the relative yields. Thus, the first hypothesis can be falsified for the yields only. The study reveals empirical evidence in favor of the second hypothesis and the spline functions of the covariates, which showed a significant relationship in the linear models. The main contribution of the study is the denial of the paradigm of *absolute* variables to explain the variation in international capital flows. Methodologically, the study enriches the literature on cross-border real estate investments by applying non-linear models to the field. These are predominantly known from hedonic pricing models of real estate assets.

Chapter 4 back tests the feasibility of the VT trading scheme to REIT positions to minimize extreme losses of the positions. Therefore, VT is applied to daily log returns of US Equity REIT positions. Since the term volatility denotes fluctuation, but neither necessarily the statistical measurement of standard deviation nor a direct relationship to historical data, the study provides interesting insights into the meaning of volatility in the context of REIT investments and its risk management. REIT returns show the essential stylized facts, such as volatility clustering and the leverage effect. Thus, the paper's first hypothesis states that VT is expected to show an economically efficient improvement in tail risk reduction. Most importantly, the empirical results show improvements in the economic efficiency of VT compared to a buy and hold strategy in a mean-$CVaR_\alpha$-optimization-framework. Thus, the first hypothesis cannot be rejected. However, the extent of the general economic efficiency is subject to the REIT subclass. Secondly, the approximation of volatility is of interest. Not only historical volatility, but also GARCH-modelled volatility, and lastly the VIX are tested because REITs are frequently seen as integrated into the broader equity markets. The second hypothesis can be rejected for the VIX, whereas the GARCH modelling of the return volatility yields the highest efficiency for at least two subclasses. Thus, a direct reproduction of historical volatility in future returns and according utilization for risk management appears feasible for REITs. Secondly, since implied volatility of the broader stock market is unbeneficial, the integration of REITs as part of the overall stock market is in doubt from a risk management point of view. Nonetheless, the abovementioned findings suggest that VT can generally be seen as an economically efficient management tool for REIT positions.

Chapter 5 back tests the one-day-ahead risk metric forecasting accuracy of the AR-GARCH-EVT-Copula compared to the variance-covariance and the historical simulation methodology for portfolios that contain securitized real estate. In addition to the previous article, not only REIT volatility dynamics are of interest, but also the co-movement patterns of REITs, stocks, and bond positions. Based on the existing literature, the hypothesis states the expectation of improvements in risk metric forecasting accuracy of the AR-GARCH-EVT-Copula model. The empirical results of the back-test show a general reduction in model hits for the AR-GARCH-EVT-Copula approach in comparison to both benchmarks across various international financial markets. Thus, there is empirical evidence in favor of the first hypothesis. The improvements are, however, subject to the chosen risk metric, because the test results indicate more substantial accuracy enhancements for the $CVaR_\alpha$ than for the VaR_α of the portfolios. The improvements are also subject to the portfolio constituents. Concerning the hypothesis, there is empirical evidence for the general existence of enhancements of AR-GARCH-EVT-Copula in comparison to the benchmarks.

Based on these individual findings, the derivation of *joint* conclusions is of interest. The first two articles can be interpreted as contributions to the literature of return and liquidity risk factors of direct real estate markets. Here, economic political uncertainty for the returns and the comparative attractiveness for foreign liquidity inflows are identified as new risk factors. These findings are especially interesting, because the specified variables are not part of classic fundamental risk factors, such as the GDP, unemployment rates, the CPI, the rent growth, etc. Thus, there is new empirical evidence for non-fundamental or comparative instead of absolute measures, which are determinants of direct real estate markets. These findings are the main economic contribution of the present thesis. Additionally, the connection of different methodological frameworks (especially GAMM from the hedonic pricing literature applied to the field of international real estate investment) contributes to the existing body of literature.

Secondly, both articles on securitized real estate positions show the *transformation* of volatility features into practicable risk management tools. Here, the market liquidity of capital markets and the high fungibility of the positions could be utilized to steer the risk exposure based on volatility measures. Additionally, the last article provides further evidence in favor of the non-linear modelling of co-movements of securitized real estate and other equity positions (as previously advocated by Knight et al., 2005), to ensure sufficient underlying capital.

Nonetheless, the research is subject to various research limitations. In sum, the present thesis does not directly provide a *comprehensive* picture of the risk management of either direct or indirect real estate positions. Still, it states insights on selected areas of the discipline. Mainly due to the clear legal requirements (in the sense of, e.g., the "*Aktiengesetz*") to establish a full risk management *system*, further research in this area may be fruitful. Turning towards the individual articles of the thesis, the evidence of the first paper is subject to data limitations. Accordingly, the data quality of cross-border investment flows in direct markets are challenging to obtain and may be in doubt since data providers are still covering relatively low percentages of transactions and thus flows. Especially limiting are the unknown capital origins and, accordingly, the missing information about the investors' regional diversification efforts (as newly addressed econometrically by Leone & Ravishankar, 2018, based on the summary of Jackson, 2013) or currency risk hedging (as recently discussed by Bejol & Livingstone, 2018).

Classification and optimization issues limit the second study on VT. The official index classification of REITs determined the portfolios. However, REITs are not necessarily holding the property types strictly according to their official classification, but also show diversification on the individual portfolio level. Thus, statements about the REIT types do not automatically apply to the assumed underlying properties. Additionally, from a methodological point of view, the portfolio optimization problem is subject to an asymmetric investment horizon because the subclasses differ by the number of REITs. This problem arises from the classification and potential survivorship bias of REITs in the categories across the entire sample duration. Since optimization comparisons should not be based on horizons containing unevenly large sets of assets, a comparison of the results across the REIT types has to be undertaken with care. Lastly, the article on the GARCH-EVT-Copula approach is mostly limited by the assumption of bivariate portfolios. Since the study uses equally weighted portfolios, containing securitized real estate and *one* other asset class, the analysis is limited to this predefined setting. Additionally, the assumption of equal weights is subject to discussion. Also, the study uses index-level data, which had to be replicated in reality. Accordingly, an extension towards multivariate portfolios can be of interest.

Future research within the fields of the present thesis can be carried out on various aspects. Concerning the general methodological challenges of direct real estate risk management, the thesis does not address the methodology itself. Especially the human user and cognitive biases are of increasing interest in the literature in combination with the MCS (as introduced by Harvard, 2001, and further investigated by Wofford et al., 2010). The recent methodological publication of Amédée-Manesme & Barthélémy (2018) is one example of the relevant literature from a corporate point of view. Additionally, the topic of *risk-related decision support systems* in real estate has moved into the center of attention for valuation (Tidwell & Gallimore, 2014) or transactions (Gleißner & Oertel, 2020). Ensuing research on cross-border investment flows in a broader sense, especially the question, if the analyzed relationship is robust to other regions or even on a global scale, can be of interest. Here the article of Devaney et al. (2019) is one current example for modelling major investment locations on a global scale as a closed investment horizon. The linkages between the underlying drivers of co-movements of investment destinations can be further investigated, as recently shown by Zhu & Lizieri (2020).

6.2 Bibliography

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