A Class of its Own: The Role of Sustainable Real Estate in a Multi-Asset Portfolio

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Abstract: In this paper, we analyze the effect of socially responsible investments within a multi-asset portfolio optimization model. We also attempt to bridge the gap in the real estate literature between sustainability principles and investment analysis. To this aim, listed real estate companies with an active sustainability agenda, identified through the MSCI ESG database, represent the sustainable real estate asset class. Applying a downside risk approach by using a conditional value at risk (CVaR) optimization technique, we establish empirically whether diversification benefits can be achieved by investing in companies with a proven track record in sustainability. Our results highlight the potential contribution of listed real estate companies with high sustainability ratings to an institutional investor’s portfolio taking into account differences in investment style and risk aversion.

The volume of socially responsible real estate investments has risen considerably over the last few years. Despite this remarkable trend, the real estate and built environment sector is still considered one of the largest contributors to greenhouse gas emissions (GHG) and climate change. The Fifth Assessment Report (IPCC AR5, 2014) of the Intergovernmental Panel on Climate Change (IPCC) states that the building sector accounts for around 32% of final energy use and for 33% of CO₂ emissions. Predictions of a doubling of energy use and a 50%–150% increase in total CO₂ emissions underline the challenges and the implied responsibility the real estate industry has to face and to take on in the next few decades (IPCC AR5, 2014). In addition to regulatory interventions by governments, real estate finance and investment is said to play a role in the shift towards a more sustainable built environment. Pension funds and insurance companies and the underlying assets they own are affected by this shift in societal awareness (Bauer, Eichholtz, Kok, and Quigley, 2011; Berry and Junkus, 2013). By definition, these institutional investors manage diversified long-term portfolios with high capital exposure, which forces them to consider and anticipate risks arising from multiple sources. The necessity to minimize the potential costs associated with these risks and/or maximize the benefits of sustainable investment opportunities gave rise to a new kind of ownership, the so-called active ownership (UNRPI, 2011a). Active ownership comprises the engagement of investors in corporate social responsibility (CSR) on a company level, not just from a shareholder perspective but also from a broader stakeholder point of view (Elroy, Karakas, and Li, 2012). Therefore, competition for investors that favor sustainable management and investments is
another key motivation for funds and other investment vehicles to “go green” behavior (USSIF, 2013).

The U.S. Sustainable Investment Forum (USSIF) expects that socially responsible investments (SRIs) will become standard by 2020 for several investor types, such as pension funds or insurance companies due to their long investment horizon. The key to more widespread adoption of environmental, social, and governance criteria (ESG) lies in their use as an additional investment attribute beside traditional financial metrics. The various SRI indices such as the Dow Jones Sustainability Index, Asset4good, and the MSCI ESG (former KLD), as well as the development of the United Nations Principles for Responsible Investment (UNPRI) demonstrates the demand for specialized financial performance metrics of sustainable investments. UNPRI signatories with assets over USD 30 trillion account for 20% of the estimated total value of global capital markets (USSIF, 2013). An increasing number of listed companies seek to be included in the SRI indices as an important signal to their stakeholders. According to a recent survey of the UNPRI (2014), 81% of respondents believe that being a UNPRI signatory brings value to their organization and 75% would recommend the benefits of being a UNPRI signatory to other institutions. Hence, both the monetary volume and the attitude of the signatories could foreshadow a further rise of responsible investment awareness.

However, to illustrate the benefits of responsible investments, not just in terms of behavior management (active ownership) but also in behavior terms of asset allocation (sustainable investing), it is important to determine how sustainable investment products perform compared to conventional investment vehicles. Sustainable products in real estate are mostly identified by green-labeled assets [i.e., certified buildings with a green building label such as LEED (Leadership in Energy and Environmental Design), BREEAM (Building Research Establishment Environmental Assessment Method) or ENERGY STAR]. The positive impact of green buildings on the financial performance of firms has been shown in several studies (Eichholtz, Kok, and Quigley, 2010; Fuerst and McAllister, 2011a, 2011b; Deng, Li, and Quigley, 2012; Cajias and Piazolo, 2013). In addition, businesses acting in line with a CSR agenda may reap financial benefits, for example a significant outperformance over the long run of sustainable companies in terms of stock market and accounting performance (Eccles, Ioannou, and Serafeim, 2013). In terms of sustainable real estate (SRE) companies, several studies find lower risk and higher financial performance for socially responsible companies (Cajias, Geiger, and Bienert, 2012; Cajias, Fuerst, McAllister, and Nanda, 2014).

Sustainability in combination with real estate and portfolio optimization has become a growing research area. A number of SRI portfolio studies indicate benefits for investors who incorporate SRI companies into their investment opportunity set. Reduced sensitivity to market fluctuations (Lee and Faff, 2009; Hoepner, Yu, and Ferguson, 2010) and/or superior returns (Bebchuk, Cohen, and Wang, 2013) have been observed consistently in these studies. In a real estate context, Geiger, Cajias, and Bienert (2013) analyze listed real estate companies in the United Kingdom within the Dow Jones Sustainability Index and find positive financial performance in terms of their risk and return characteristics.
By and large, the popularity of sustainable investment vehicles is driven by societal awareness, mounting pressure on the real estate industry to act in accordance with climate change mitigation goals, steadily growing demand for SRIs, investor interest in active ownership, and the potential for asset allocation diversification benefits. A competitive environment within the investment industry is further pushing the market players to introduce sustainable investments to achieve possible performance advantages (Prakash, 2005; Galasso and Tombak, 2014).

In this paper, we analyze the behavior of listed real estate companies acting in accordance with a sustainability agenda within a multi-asset portfolio and their investment characteristics for institutional investors. The principal aim of this analysis is to broaden the knowledge about the field of SRE in a multi-asset portfolio optimization context evaluating the financial performance implication from a U.S. investor perspective. The remainder of this paper is organized as follows: A review of the theoretical background discloses the status quo in the SRI universe with a focus on SRE together with the theoretical approach. Secondly, the composed SRE index based on the MSCI ESG is presented. Thirdly, the opportunity set for the multi-asset portfolio optimization is defined from a U.S. investor perspective. Fourthly, the applied optimization methodology and analysis of the results is presented, followed by a discussion of the implications. The concluding remarks put the results in the context of the larger SRI market behavior.

Current State of Research

In the previous section, we underlined that there is a plethora of initiatives, organizations, and acronyms that are active in the sustainable investment arena. Hence, there is no universally accepted definition of what constitutes a sustainable investment. The common current research opinion is a multi-dimensional approach taking social, environmental, and economic concerns in equal measures into account (Elkington, 1998). Concepts such as CSR, SRI, and ESG are part of the nomenclature of sustainable investing.

The U.S. market played a pioneer role in the field of sustainable investments with its beginnings in the 1990s (Newell, 2008; Ritter, 2008). Starting with mutual funds that pursued a dedicated CSR investment strategy, sustainability reporting rapidly gained momentum, not least initiated by institutional investors putting pressure on funds and investment managers to act sustainably and put a transparent reporting system in place. Due to the fact that the exposure to social, environmental, and governance issues varies widely across industries, multi-sector studies can conceal or average out sector-specific effects (Griffin and Mahon, 1997). Following a similar logic, Chand (2006) suggests that research on the link between sustainability performance and financial performance should focus on a single industry. In the real estate industry, a number of quantitative studies examined the financial performance characteristics of sustainable labelled buildings in the U.S. revealing rent premiums ranging between 2% and 17% (Pivo and Fisher, 2010; Wiley, Benefield, and Johnson, 2010; Fuerst and McAllister,
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2011a, 2011b; Reichardt, Fuerst, Rottke, and Zietz, 2012; Eichholtz, Kok, and Quigley, 2013), higher sales values up to 13% (Eichholtz, Kok, and Quigley, 2013) or increased occupancy rates ranging between 0.2% and 18% (Fuerst and McAllister, 2009; Pivo and Fisher, 2010; Wiley, Benefield, and Johnson, 2010). Decreasing operating costs by around 30% (Pivo and Fisher, 2008; Miller, Benefield, and Johnson, 2008), higher net operating income up to 5.9% as well as lower capitalization rates (Miller, Spivey, and Florance, 2008; Pivo and Fisher, 2008; IPD, 2011) and productivity gains (Loftness et al., 2003) report further possible advantages of sustainable actions on a property level.

The effect of sustainability on a company’s performance is contemporary, as shown in several studies. Mistra (2008) states the potential for major reputation and brand growth, which is reinforced by the studies of Pivo and Fisher (2010), Eichholtz, Kok, and Quigley (2013), and Cajias, Fuerst, and Bienert (2014), who describe the direct and indirect financial benefits for companies with a sustainability agenda. Bauer, Eichholtz, and Kok (2011), Cajias and Bienert (2011), and Cajias, Geiger, and Bienert captured effects like decreasing idiosyncratic risk, increased ability to generate revenues (i.e., a positive relationship between financial performance and sustainability for real estate companies). Although Cajias, Fuerst, and Bienert (2014) find a positive effect in terms of market value and a high overall sustainability rating (ESG-rating, using MSCI ESG database), the distinction between sustainability strengths and concerns triggers the strongest effect. Consequently, a low sustainability rating significantly depresses the market value of a company. However, the effect of the sustainability rating on returns indicates that a high number of sustainability concerns appear to affect the return positively. Questions about timing, lagging or acquisition issues arose in these studies as possible explanations and motivation for further research. Additionally, Eichholtz, Kok, and Yonder (2012) found for U.S. real estate investment trusts (REITs) that the “greenness” of REIT portfolios is positively linked to the operating performance such as return on assets, return on equity, and the ratio from funds from operations to total revenue as well as lower market betas. Abnormal returns have not been noticed.

The idea of bundling SRE companies in an index and setting them into a multi-asset portfolio optimization framework is still relatively new territory for researchers. The basis for portfolio optimization techniques examining the behavior of real estate has already been extensively done by Geltner (1993), Fisher (1994), Seiler, Webb, Myer, and Neil (1999), Bond and Patel (2003), Coleman and Mansour (2005), Seiler and Seiler (2005), and Estrada (2008) revealing the specific asset characteristics, but not within a sustainability context. Based on studies outside the real estate industry using sustainable companies within a multi-asset portfolio, effects such as lower sensitivity to market fluctuations of the portfolio, existence of superior returns or decreasing information asymmetry appeared (Statman, 2006; Hoepner, Yu, and Ferguson, 2010; Derwall, Kojedijk, and Horst, 2011; Borgers, Derwall, Koedijk, and Horst, 2012; Cho, Lee, and Pfeiffer, 2013; McIntosh and Brzeszczynski, 2013; Rathner, 2013). SRE-specific portfolio research appears in the study of Geiger, Cajias, and Bienert (2013), who find a unique risk-return pattern with allocations in virtually all portfolios with
varying risk levels up to the point where SRE is allocated as the main asset class. The SRE data were based upon the Dow Jones Sustainability Index for this U.K. case study.

The optimization model applied in this paper is a percentile risk measure and is defined as the conditional expected loss under the condition that it exceeds the value at risk (VaR) (Rockafellar and Uryasev, 2000), called conditional value at risk (CVaR). The model is not routinely applied in the finance industry, mainly due to its complexity, although it allows for effective handling of time series data.

**Sustainable Real Estate in the U.S.—MSCI ESG Data**

Harmonizing and standardizing existing sustainability indicators ranks highly on the agenda of sustainability benchmark service providers. The principal aim is to make sustainability performance measurable and comparable across companies and over time. Several rating agencies are now active in the market and try to capture sustainability performance with independent measures comparable to credit rating agencies. These ratings create transparency and provide valuable information for investors and managers wishing to invest in sustainable assets above and beyond the standard financial metrics (USSIF, 2013).

In general, a rating can include a company’s past performance and/or companies’ future potential to expand their sustainability action (Chatterji, Levine, and Toffel, 2009). However, criticism was expressed concerning the quality and transparency of the criteria, the lack of robust evaluation, and the arbitrariness and inconsistency of selection criteria (Hawken, 2004). The present study is based on the MSCI ESG database, former called KLD Index. Developed by Kinder, Lydenberg, and Domini and Co. (KLD), the KLD index is one of the longest established sustainability rating indices. The rating is a proprietary system with seven sustainability areas, such as community relations, corporate governance, diversity, employee relations, environment, human rights, and products. While the number of indicators has varied over time, the index generally accounts for 80 indicators. The sustainability performance is calculated by major strength, minor strength, major weakness, minor weakness, etc. as the index serves as the basis for publicly available sources, other data organizations, direct communication with companies themselves, and government information. Note that the publishing date of the annual rating is after the end of the calendar year when some information is already priced in the market and some are considering the new overall sustainability rating score.

Since the MSCI ESG changes the number of criteria over time, the ratio of possible scoring points on strengths versus concerns, a rating index controlling for the artificial variations is difficult to construct and apply. Developing at the beginning a summary measure of an overall sustainability performance $ESG_i$, equation (1) shows the combination of the individual information of strength and concerns:
where $S_{it}$ and $C_{it}$ are individual binary strength and concern ratings for real estate company $i$ at time $t$ and the denominators $S_t$ and $C_t$ represent the total number of rating criteria respectively in a given year. This equation ensures the comparability over time, notwithstanding changing numbers of strength and concerns over the years. A neutral position is achieved by a score of 50 relative to strength and concerns; a score above 50 represents more strengths than concerns and a score below 50 more concerns than strengths. Overall, this ESG index creates an aggregate continuous score from simple binary variables, which ensures comparability both across companies and across time (Cajias, Fuerst, McAllister, and Nanda, 2014; Cajias, Fuerst, and Bienert, 2014).

However, the simple aggregate ESG index has been criticized for assigning equal weights to all ESG criteria (Griffin and Mahon, 1997; Simpson and Kohers, 2002). This criticism is particularly relevant in our study on sustainable real estate, which renders some of the general criteria irrelevant (e.g., investments in firearms or nuclear energy) while others (e.g., clean energy and climate change mitigation) should obtain larger weights in the real estate index. Hence we propose the following weighted index scoring formula:

$$ESG_{it} = \left( \frac{\sum_{j=1}^{n} S_{it} * 100}{S_t} * 100 - \frac{\sum_{j=1}^{n} C_{it} * 100}{C_t} * 100 + 100 \right) / 2,$$

(1)

where $S_{it}$ and $C_{it}$ are individual binary strength and concern ratings for real estate company $i$ at time $t$ multiplied by the criterion weights $w_{jt}$. In this index, a score of 1 represents a neutral position, where strengths and concerns balance each other out. A score below 1 indicates more concerns than strengths and vice versa for scores above 1.

The weights in equation 2 are derived by the following:

$$w_{jt} = \frac{\sum_{j=1}^{n} S_{it} + \sum_{j=1}^{n} C_{it}}{\sum_{j=1}^{n} \sum_{j=1}^{n} S_{it} + \sum_{j=1}^{n} \sum_{j=1}^{n} C_{it}}.$$

(3)
The weight of an sustainability criterion in year $t$ is based on the sum of individual binary counts for all real estate companies for this criterion over the sum of all criteria and real estate companies in that year. Accordingly the weight of a criterion is constituted by the number of non-zero weightings for real estate companies in a particular year. This procedure allows asymmetry in terms of strengths and concerns to the extent that the sum of weights of strengths does not need to equal the sum of weights of concerns. The weighting scheme is in principle equivalent to a Paasche current-weighted index in that the individual weights of the criteria vary from year to year. Determining the companies that will be included in the CVaR optimization framework, a sustainability scoring over 1 is decisive (i.e., high sustainable performing companies are incorporated in the multi-asset optimization). This ensures the classification sustainable and allows us to differentiate SRE from the other “non-sustainable” asset classes.

The dataset employed in this study is merged with the CUSIP codes of the firms incorporated in the MSCI ESG database and Thomson Reuters Datastream. An algorithm to address database matching issues was employed to ensure the consistency of companies included in both MSCI and Datastream. ICB industry classification codes, used by Thomson Reuters Datastream, helped to identify different real estate sectors.

The created real estate sustainability index contains the following sectors: mortgage REITs, retail REITs, industrial and office REITs, specialty REITs, residential REITs, hotel and lodging REITs, real estate holdings and developers, real estate services, and diversified REITs. Exhibit 1 provides a sector overview of the year 2010 with company weightings.
The overall sample consists of 341 real estate companies in an unbalanced sample from 2003 to 2010. Employing companies with a score over 1, hence high sustainability performing companies, the number of companies in the index gets reduced and varies each year (e.g., 86 companies are included 2010). Subsequently, the real estate sample is dynamic and applied in the CVaR portfolio optimization framework.

**Data Description**

The opportunity set of the multi-asset portfolio consist of seven asset classes in the U.S. market. Beside the developed sustainable real estate index described above, large cap equities, small cap equities, public real estate, long-term government bonds, long-term corporate bonds, and cash are included. The opportunity set constitutes a menu of asset classes typically preferred by institutional investors for strategic risk diversification. The timeframe is eight years covering January 2003 to December 2010, for which a consistent MSCI ESG database is available. In order to analyze the behavior of sustainable real estate over time, rolling portfolios were modeled starting in month $t_{36}$ and computed for every observation up until $t_{96}$. With the exception of MSCI ESG data, all asset data were collected from Thomson Reuters Datastream. The general stock market is represented by the S&P 500 Composite Series, whereas the S&P 600 Small Cap series mirrors the performance of small cap stocks. The FTSE NAREIT U.S. Equity Index serves as the proxy for publicly traded real estate. Long-term government bonds as well as long-term corporate bonds with a duration of 10 years are represented by the Citigroup U.S. Government Bond Index and the Citigroup U.S. Corporate Bond Index. Operational liquidity is reflected by the J.P. Morgan U.S. 3-month cash index.

**The Concept of a Conditional Value at Risk Portfolio Optimization**

The VaR of a random variable $X$, such as a return time series, is expressed as the smallest loss in the $(1 - \alpha) \times 100\%$ worst cases. In other words, the VaR is the minimum loss that will not be exceeded by probability $\alpha$. The CVaR, in contrast, corresponds to the expected loss, conditional on the fact the loss exceeds the VaR at a given $\alpha$-level, as illustrated in Exhibit 2.

The empirical framework is based on a CVaR approach, which is a standard tool for risk-return analysis. The CVaR replaces the covariance matrix as risk measure in a portfolio optimization and is known as mean shortfall, mean excess loss or tail value at risk. More specifically, CVaR is the conditional expectation of the loss above VaR for the time period, as well as for the confidence level under consideration. Rockafellar and Uryasev (2000) stated the advantages of using the CVaR within a portfolio optimization context as follows: Coherent risk measure, sub-additive, convex, and near optimal solutions in VaR terms. Because of $\text{CVaR} \geq \text{VaR}$, the optimization, formally, minimizes not just the CVaR, it also
lowers the VaR and is considered by Rockafellar and Uryasev (2000) as well as Acerbi and Tasche (2002) as a more consistent measure of risk than VaR. More recent risk metrics such as Shalit’s (2014) Lorenz curve analysis also build on the CVaR approach. Equivalent linear constraints are applied to improve the efficiency of the optimization technique. The mathematical formulation is a mean-CVaR optimization problem representing an equivalent linear programming problem. Contrary to a mean-variance portfolio optimization, there are no longer restrictions concerning a multivariate elliptically contoured distribution of the asset set. The theoretical background of a CVaR portfolio optimization used here is based on the model of Pflug (2000) and Rockafellar and Uryasev (2000). Let \( \Psi \) denote the cumulative distribution function for the loss associated with \( \omega \) as:

\[
\Psi(\omega, \gamma) = \int_{f(\omega, r) \leq \gamma} p(r)dr.
\]  

(4)

Considering a portfolio of assets with random returns, the portfolio vector of weights is denoted with \( \omega \) and the random events by the vector \( r \). The term \( f(\omega, r) \) is the loss function when choosing the portfolio \( W \) from a set \( X \) of feasible portfolios. \( r \) is the realization of the events and has a probability density function denoted by \( p(r) \). Given a fixed decision vector \( \omega \), the cumulative distribution function of the loss given the vector \( \omega \) can be optimized. Further, for a given confidence level \( \alpha \), the VaR associated with portfolio \( W \) is written in as:

\[
\text{VaR}_\alpha(\omega) = \min \{ \gamma \in \mathbb{R} : \Psi(\omega, \gamma) \geq \alpha \}.
\]  

(5)
The CVaR$_\alpha$ of portfolio $W$ is defined as:

$$CVaR_\alpha(\omega) = \frac{1}{1 - \alpha} \int_{f(\omega, r) \geq VaR_\alpha(\omega)} f(\omega, r)p(r)dr.$$  \hspace{1cm} (6)

The optimization problem of the mean-CVaR portfolio selection is computed under the restriction that the portfolio target return equals $\tilde{r}(\omega^T \mu = \tilde{r})$ and that the sum of relative allocations across the assets equals 1 ($\omega^T 1 = 1$) in (7) as:

$$\min_{\omega} CVaR_\alpha(\omega) \text{w.r.t.} \left(\omega^T \mu = \tilde{r}, \omega^T 1 = 1\right).$$ \hspace{1cm} (7)

Solving the mean-CVaR portfolio, the following equation gets applied:

$$F_\alpha(\omega, \gamma) = \gamma + \frac{1}{1 - \alpha} \int (f(\omega, r) - \gamma)^+ p(r)dr.$$ \hspace{1cm} (8)

This is the final function of $\gamma$ with following attributes being advantageous for calculating VaR$_\alpha$ and CVaR$_\alpha$: $F_\alpha(w, \gamma)$ is convex function of $\gamma$; VaR$_\alpha(w)$ is a minimizer of $F_\alpha(w, \gamma)$; and the minimum value of the function $F_\alpha(w, \gamma)$ is CVaR$_\alpha(w)$.

The optimization of the term $\int (f(\omega, r) - \gamma)^+ p(r)dr$ is a complex numerical problem extensively explained Rockafellar and Uryasev (2000) in order to satisfy the condition that CVaR $\geq$ VaR. The portfolio optimization was solved with R (2016) by either minimizing the CVaR or maximizing the return. Recall that the portfolio optimization with $\alpha = 0\%$ corresponds to the unconstrained traditional mean-variance optimization problem. Four different confidence intervals have been applied starting with $\alpha = 0$ (0%-CVaR), $\alpha = 0.010$ (1%-CVaR), $\alpha = 0.050$ (5%-CVaR), and $\alpha = 0.100$ (10%-CVaR). The ability to apply several constraints with varying confidence levels and shapes in the loss distribution matching the investment preferences of investors are attractive features for portfolio optimization (Korkhmal, Palmquist, and Uryasev, 2002). Furthermore, 12 portfolios ranging from a portfolio return of 0.1% ($r = 0.001$) up to 1.2% ($r = 0.12$) monthly allow us to illustrate the asset allocation for investors with varying return requirements (i.e. risk averse, risk aware and opportunistic investors). Subsequently, the CVaR approach appears to be appropriate for analyzing the behavior of SRE within a multi-asset context taking different investor risk-return specifications into account by minimizing the mean excess loss for a given return profile. Tracking the behavior of the assets, particularly for SRE, rolling portfolios were calculated from month $t_{36}$ until $t_{96}$ running the CVaR optimization for both the confidence interval and the return level. The aim of the CVaR optimization is...
Summary Statistics

Sustainable real estate does not appear to yield high returns, but is also not exposed to excessively high risk as measured by variance. This is demonstrated by the summary statistics in Exhibit 3. This could indicate an allocation in low-return portfolios. Public real estate reveals the highest return, followed by small caps, large caps, long-term government and corporate bonds in congruence with the risk ranking in the same order, except for long-term government and corporate bonds where it is the other way around. The CVaR model allows for skewness, which seems appropriate since returns do not show a normal distribution. The Jarque-Bera test presents the significance of non-normal distributed returns and confirms the application of a CVaR optimization, since all assets show non-normal distributions (i.e., Jarque-Bera over 6). The CVaR approach allows, despite the distribution problem, for an optimal asset allocation.

In Exhibit 4, SRE is lowly correlated with every other asset class within the opportunity set. This can be expected to play a major role for the allocation process and bodes well for possible diversification benefits. Public real estate in contrast has a strong correlation with the equity market assets, such as large and small caps. However, considering that over 90% of the companies included in the MSCI ESG index are REITs and close to the equity market environment, this correlation gap between SRE and public real estate is an interesting finding. This is possibly triggered by the implied sustainability aspect of the corporations and their inherent investment style (long-term investment instead of short profit buying/selling) and/or investor type (active ownership/“stickier” behavior). The high correlation between long-term government and corporate bonds as well as...
the low correlation of bonds to the equity market is in line with investment theory. Although SRE seems less suitable for high return seeking investors, SRE becomes attractive when diversification matters. Investor preferences in terms of return requirements will then determine the allocated percentage of SRE within several portfolios in the subsequent analysis.

**Sustainable Real Estate Behavior in a CVaR Portfolio**

The focus of the optimization is on the behavior of SRE within the framework of seven asset classes, four different confidence intervals starting with \( \alpha = 0 \) (0%-CVaR), \( \alpha = 0.010 \) (1%-CVaR), \( \alpha = 0.050 \) (5%-CVaR), and \( \alpha = 0.100 \) (10%-CVaR), 12 different structured target return portfolios (0.1%, \( r = 0.001 \) up to 1.2%, \( r = 0.012 \)), minimized CVaR, and the dynamic process analyzed by rolling portfolios from \( t = 36 \) to \( t = 96 \). For simplification of nomenclature, the portfolios I–IV (\( r = 0.001 \) to \( r = 0.004 \)) are called low return, V–VIII (\( r = 0.005 \) to \( r = 0.008 \)) medium return, and IX–XII (\( r = 0.009 \) to \( r = 0.012 \)) high return portfolios. The structure of the empirical analysis is as follows: (1) the CVaR of the opportunity set assets with varying confidence intervals; (2) the efficient frontier of the CVaR portfolio optimization for the optimized portfolios I–XII with target returns, varying confidence levels and minimized CVaR; (3) the CVaR optimal asset allocation within the portfolios I–XII with target returns, varying confidence levels and minimized CVaR; and (4) the allocation of SRE within the optimal portfolios I–XII in a rolling portfolio framework to analyze the behavior of SRE.

**The Assets CVaR**

The results in Exhibit 5 show the CVaR for all seven assets under the condition of four \( \alpha \) confidence levels. The results reveal the lowest CVaR is basically consistent for SRE in every confidence level, beside cash. Keeping the results of the descriptive statistics in Exhibit 2 in mind, especially the variance, the ranking of the assets is similar. Starting with the highest CVaR, the ranking is public real
Exhibit 5 | CVaR-Quantiles with Different Confidence Levels for Every Asset: 2003:M1–2010:M12

<table>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0% CVaR</td>
<td>0.1580</td>
<td>0.2482</td>
<td>0.3280</td>
<td>-0.0814</td>
<td>-0.0949</td>
<td>0.0002</td>
</tr>
<tr>
<td>1% CVaR</td>
<td>-0.0334</td>
<td>-0.0511</td>
<td>-0.0671</td>
<td>-0.0286</td>
<td>-0.0260</td>
<td>0.0002</td>
</tr>
<tr>
<td>5% CVaR</td>
<td>0.0109</td>
<td>0.0151</td>
<td>0.0266</td>
<td>0.0039</td>
<td>0.0065</td>
<td>0.0017</td>
</tr>
<tr>
<td>10% CVaR</td>
<td>0.1122</td>
<td>0.1624</td>
<td>0.2974</td>
<td>0.1111</td>
<td>0.1560</td>
<td>0.0050</td>
</tr>
</tbody>
</table>

Exhibit 6 | Portfolios with CVaR for Different Confidence Levels and Given Returns: 2003:M1–2010:M12

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Return</th>
<th>1% CVaR</th>
<th>5% CVaR</th>
<th>10% CVaR</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.1%</td>
<td>6.11%</td>
<td>3.69%</td>
<td>2.64%</td>
</tr>
<tr>
<td>II</td>
<td>0.2%</td>
<td>2.68%</td>
<td>2.26%</td>
<td>1.89%</td>
</tr>
<tr>
<td>III</td>
<td>0.3%</td>
<td>2.70%</td>
<td>2.34%</td>
<td>1.90%</td>
</tr>
<tr>
<td>IV</td>
<td>0.4%</td>
<td>3.97%</td>
<td>3.19%</td>
<td>2.26%</td>
</tr>
<tr>
<td>V</td>
<td>0.5%</td>
<td>5.24%</td>
<td>4.08%</td>
<td>2.81%</td>
</tr>
<tr>
<td>VI</td>
<td>0.6%</td>
<td>6.50%</td>
<td>4.98%</td>
<td>3.49%</td>
</tr>
<tr>
<td>VII</td>
<td>0.7%</td>
<td>8.34%</td>
<td>5.90%</td>
<td>4.18%</td>
</tr>
<tr>
<td>VIII</td>
<td>0.8%</td>
<td>13.04%</td>
<td>7.23%</td>
<td>5.04%</td>
</tr>
<tr>
<td>IX</td>
<td>0.9%</td>
<td>17.73%</td>
<td>9.40%</td>
<td>6.48%</td>
</tr>
<tr>
<td>X</td>
<td>1.0%</td>
<td>22.43%</td>
<td>11.82%</td>
<td>8.45%</td>
</tr>
<tr>
<td>XI</td>
<td>1.1%</td>
<td>30.32%</td>
<td>16.21%</td>
<td>12.01%</td>
</tr>
<tr>
<td>XII</td>
<td>1.2%</td>
<td>32.80%</td>
<td>18.92%</td>
<td>13.57%</td>
</tr>
</tbody>
</table>

estate, small caps, large caps, long-term corporate bonds, and long-term government bonds. Pointing out the CVaR of real estate companies with a sustainability focus, a low CVaR indicates (i.e., a low tail VaR) what is triggered by the return shape. The hypothesis that sustainable actions within real estate corporations positively influences the expected shortfall.

CVaR Efficient Frontiers with Optimal Portfolio Asset Allocations

We compute three types of efficient frontiers and the results are shown in Exhibit 6. The risk and return diagram is shown in Exhibit 7, where the efficient frontier shapes are presented in a graph with return on the abscissa and CVaR on the ordinate.
Exhibit 7 | Efficient Frontier with CVaR for Different Confidence Levels and Target Returns: 2003:M1–2010:M12

Efficient Frontiers

Conditional Value at Risk

Target Return
In line with CVaR theory, the higher the confidence level, the higher the VaR [i.e., \(99\% (1 - \alpha 0.001) > 95\% (1 - \alpha 0.005)\)] and subsequently the CVaR of the portfolio optimization. The 1%, 5%, and 10% CVaR columns illustrate the minimized CVaR. This means, for example, that for portfolio V with a portfolio target return of 0.5%, the average loss in 1%, 5% or 10% worst cases must not exceed 5.24%, 4.08% or 2.81% of the initial portfolio value, respectively. As a matter of course, the higher the expected return, the higher the risk tolerance in CVaR. The question arises as to which asset gets allocated into what portfolio and what role does SRE play in all portfolio optimization scenarios?

**CVaR Optimal Asset Allocation Weights and the Sustainable Real Estate Behavior**

Our analysis has demonstrated the optimal asset allocations over the whole time period from January 2003 to December 2010. Exhibits 8 to 11 show the given portfolio target return on the y-axis of Portfolios I–XII while the x-axis shows the respective share of the assets allocation. The optimal portfolios are constructed from low return with \(r = 0.001\) monthly in 0.1% steps until the maximum
achievable return $r = 0.012$ (i.e., the asset with the highest return gets exclusively allocated). Cash is allocated with a 5% maximum. This constraint is based on the assumption that investors hold a certain amount of their capital out for liquidity reasons.

The first optimization set, shown in Exhibit 8, is without a CVaR constraint (i.e., with $\alpha = 0\%$), corresponding to the unconstrained traditional mean-variance optimization. An SRE-only portfolio is allocated in the low return portfolio with decreasing allocation percentages up to the highest return portfolios, due to their low correlation with the remaining assets. Public real estate allocation is increasingly commensurate with the required portfolio return for public real estate only in Portfolio XII. Cash is continuously allocated with a marginal amount, also triggered by the 5% maximum constraint in the low return portfolios. Long-term corporate bonds as well as large caps are allocated predominantly in the low return area. Small caps and long-term government bonds do not form part of the optimal portfolio. The behavior of SRE in a 0%-CVaR optimization seems to be similar to research by Geiger, Cajias, and Bienert (2013) focusing on the U.K., where SRE acts as a main asset class in mid to high return portfolios, and is also well...
allocated in low-yielding portfolios. Perhaps surprisingly, because of the different risk-return pattern of the Dow Jones Sustainability Index compared to the MSCI ESG. Hence, we test how the predicted allocations of sustainable real estate change when several CVaR constraints are introduced.

Taking now varying confidence levels into account, a different picture emerges. Exhibit 9 shows the optimal asset allocation for the given target returns and a confidence level of 99% over the whole timeframe. The most conspicuous finding is the allocation of SRE in high return portfolios as well as the allocation of public real estate exclusively to the high return portfolios. The incorporation of the hitherto missing assets into long-term government bonds as well as small caps is also noticeable. The CVaR approach demonstrates through the implied confidence level that a downside risk model introduces further assets into the optimal portfolio and triggers diversifying effects for investors. This means, although assets may offer high volatility, the CVaR approach differentiates between positive upward and negative downside return movements. Therefore, SRE behaves in a CVaR context as a main asset class in low-yielding portfolios and as a diversifier in medium-yielding portfolios. The allocation shift is triggered through the

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**Exhibit 10 | CVaR Optimal Portfolio Asset Allocations, $\alpha = 0.05$, Confidence Level = 95%, 2003:M1–2010:M12**
incorporation of these asset classes and their CVaR attributes. The introduction of CVaR constraints demonstrates more realistically the allocation advantage of SRE for investors with low- to medium-yielding portfolio requirements. Applying higher alphas (i.e., lower CVaR confidence levels), the result is shown in Exhibit 10 with a 95% confidence level and Exhibit 11 with a 90% confidence level.

A relatively constant allocation to SRE is perceivable in the low- to medium-yielding portfolios. In the case of long-term government and corporate bonds as well as for public real estate and small caps, higher allocations shifts can be observed.

Focusing on SRE allocations, the portfolio allocations are given in Exhibit 12. Similar to Exhibits 8–11, the percentage of SRE allocated within the varying return portfolios decreases in the CVaR model. However, SRE stays in the low return portfolios of I–IV and is quite stable at every CVaR confidence level and increases in the 5% CVaR and 10% CVaR cases compared to the 1% CVaR in the medium return portfolios of V and VI.
### Exhibit 12

Optimal SRE Allocations for 0% CVaR, 1% CVaR, 5% CVaR, and 10% CVaR:
2003:M1–2010:M12

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Return</th>
<th>0%-CVaR</th>
<th>1%-CVaR</th>
<th>5%-CVaR</th>
<th>10%-CVaR</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.10%</td>
<td>98.72%</td>
<td>98.72%</td>
<td>98.72%</td>
<td>98.72%</td>
</tr>
<tr>
<td>II</td>
<td>0.20%</td>
<td>74.73%</td>
<td>74.69%</td>
<td>74.17%</td>
<td>75.03%</td>
</tr>
<tr>
<td>III</td>
<td>0.30%</td>
<td>67.25%</td>
<td>59.19%</td>
<td>58.21%</td>
<td>58.66%</td>
</tr>
<tr>
<td>IV</td>
<td>0.40%</td>
<td>63.04%</td>
<td>42.86%</td>
<td>47.46%</td>
<td>46.18%</td>
</tr>
<tr>
<td>V</td>
<td>0.50%</td>
<td>56.32%</td>
<td>26.53%</td>
<td>35.16%</td>
<td>33.87%</td>
</tr>
<tr>
<td>VI</td>
<td>0.60%</td>
<td>46.55%</td>
<td>10.19%</td>
<td>21.01%</td>
<td>15.61%</td>
</tr>
<tr>
<td>VII</td>
<td>0.70%</td>
<td>36.79%</td>
<td>0.00%</td>
<td>5.84%</td>
<td>0.00%</td>
</tr>
<tr>
<td>VIII</td>
<td>0.80%</td>
<td>27.02%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>IX</td>
<td>0.90%</td>
<td>17.25%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>X</td>
<td>1.00%</td>
<td>7.48%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>XI</td>
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<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>XII</td>
<td>1.20%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

### Exhibit 13

Rolling Portfolio: 0% CVaR Optimal Portfolio SRE Allocation, alpha = 0,
Confidence Level 1-0 = 1, 2003:M1–2010:M12
Exhibit 14 | Rolling Portfolio: 1% CVaR Optimal Portfolio Asset Allocations, alpha = 0.01, Confidence Level 1-0.01 = 99%, 2003:M1–2010:M12

Exhibit 15 | Rolling Portfolio: 5% CVaR Optimal Portfolio Asset Allocations, alpha = 0.05, Confidence Level 1-0.05 = 95%, 2003:M1–2010:M12
In summary, the fairly continuous allocation of SREs to a multi-asset portfolio of various risk-return profiles with different confidence levels constitutes our main finding. Another interesting observation is the role of SRE as a dominating asset class in low return portfolios. The allocation between 10% in a 1% CVaR, 21.01% in a 5% CVaR, and 15.61% in a 10% CVaR portfolio in the medium return sector underpins the attractiveness of SRE companies within an investor’s portfolio seeking a medium return. Overall, SRE has the chance to evolve into an asset class catering to risk-averse investors and offers an additional diversifying alternative to medium-return investors. However, the opportunistic high-return investor is unlikely to seek SRE investments.

**Rolling Portfolios and the Behavior of SRE over Time**

The past investment performance of SRE provides valuable insights into their dynamics over time. Portfolios I–XII are computed for every confidence level starting uniformly in \( t_{36} \) up to \( t_{96} \). Exhibits 8 to 11 illustrate the asset allocation of SRE for every point in between the applied time frame and reveal an interesting reverse pattern within the portfolio allocations. Up until \( t_{50} \), SRE has a high allocation (i.e., between 30% and 50%), in contrast to the medium to high return portfolios up to \( t_{96} \), which are characterized by rather small allocations in the lowest return portfolios. The allocations between the low to medium return portfolios decrease as well over time, but are still at relatively high levels. Closer inspection of the portfolios reveals a noticeable structural allocation shift from \( t_{51} \).
to $t_{69}$. SRE allocations diminish out of the portfolios with a required return of $r = 0.007$ up to $r = 0.012$. Beyond this point, the allocation of SRE ranges consistently between the low ($r = 0.001$) to medium return portfolios ($r = 0.006$). The variation in confidence levels shows relatively small differences. Bearing in mind a structural break appears in $t_{69}$, with the onset of Global Financial Crisis. It seems that SRE was also affected by the rapid and precipitous re-valuation of assets to their fair levels. The U.S. index appears to lead the U.K. index in this regard.

**Conclusion**

The real estate investment business is often characterized as being driven purely by financial metrics. However, there is an increasing trend towards greater accountability and transparency, not least with regard to the environmental and social impact of these investments. In this context, the effect of sustainability at the individual real estate asset and company level has been demonstrated by a number of studies. In this study, we investigated whether positive sustainability attributes may also make a positive contribution to an investor’s optimal portfolio set and if so, which types of investors should consider introducing sustainable real estate into their portfolio.

The conditional-value-at-risk (CVaR) approach was employed to test the optimal asset allocation under realistic investor preferences taking advantage of a downside risk treatment and displaying risk just in terms of a negative volatility. Sustainable real estate (SRE) exhibited relatively low returns, at least in recent years. Applying the CVaR framework indicated the significant role of SRE within multi-asset portfolio optimization with a high allocation in low return portfolios. Conversely, high-yielding portfolios are unlikely to incorporate large shares of SRE investments. As a corollary of these findings, it appears that risk-averse investors may benefit from including SRE as a distinct asset class in their investment decisions. For medium return seeking investors, SRE may act as a diversifier due to its favorable return-CVaR characteristics. Opportunistic investors are unlikely to introduce SRE into their investment portfolios.

Our analysis of SRE leads to the conclusion that a distinct asset class has evolved over the last decade, which broadens the investment opportunity set for U.S. and international market participants. Rolling portfolio windows highlighted the finding that SRE dominated medium to high return portfolios while acting as a diversifier in low return portfolios. However, a structural break is observed since the onset of the Global Financial Crisis with SRE allocations changing from a relatively high return/high risk asset class to a low return and more risk-averse asset class. Several possible explanations can be offered for this shift, primarily a potential adjustment to fair value after an initial period of market euphoria, the increased transparency of the sustainability investment market and, perhaps most importantly, the heightened acceptance of and commitment to sustainable investing in mainstream investment and finance, all contributing to the maturing of the SRE market segment.
Appendix

Exhibit A1 | Rolling Portfolio: 0% CVaR Optimal Portfolio SRE Allocation, $\alpha = 0$, Confidence Level = 1, 2003:M1–2010:M12
Exhibit A2 | Rolling Portfolio: 1%-CVaR Optimal Portfolio Asset Allocations, $\alpha = 0.01$, Confidence Level = 99%, 2003:M1–2010:M12
Exhibit A3 | Rolling Portfolio: 5% CVaR Optimal Portfolio Asset Allocations, $\alpha = 0.05$, Confidence Level = 95%, 2003:M1–2010:M12
Exhibit A4 | Rolling Portfolio: 10% CVaR Optimal Portfolio Asset Allocations, \( \alpha = 0.10 \), Confidence Level = 90%, 2003:M1–2010:M12

References


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