ACADEMIC RESEARCH

The Volatility of Listed Real Estate in Europe and Portfolio Implications

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EXECUTIVE SUMMARY

During the past 20 years, European listed real estate experienced three bear markets: the global financial crisis and its aftermath leading to the European sovereign debt crisis, the COVID-19 pandemic, and the Ukraine conflict and subsequent periods of increasing inflation. For example, listed real estate prices in Europe decreased by 78% from their maximum to their minimum during the global financial crisis. These large price fluctuations are a major concern for investors, as they have a disproportionate impact on volatility and downside risk which are important considerations when constructing a portfolio. As such, it is important to understand how these large price movements vary over time and across sectors and/or countries.

Going beyond strategic asset allocation, the price volatility, but also the deviations from net asset value that it generates, may be used as inputs to devise tactical rebalancing strategies. The sharp reaction of some listed real estate sectors to unforeseen events suggests that volatility spikes may provide entry points at favorable price levels that could be exploited for such purposes. A price decline relative to net asset value could also constitute an attractive price level.

Against this background, this paper analyzes how the volatility of European listed real estate across sectors and countries has changed during the period 2003-2022. We also study how this information, as well as deviations from net asset value, can be used in a dynamic portfolio framework. Our focus is on the main sectors (office, retail, residential, industrial, and diversified) and countries (Germany, the U.K., Switzerland, Sweden, France, and Belgium) of the listed market. To assess how the volatility of European listed real estate has changed over time and space, we estimate conditional volatilities and then identify high and low volatility regimes. We then investigate the impacts of rule-based tactical rebalancing on the performance and composition of a listed real estate portfolio. For this, we consider five strategic allocation approaches (i.e., equally-weighted, capitalization-weighted, maximum Sharpe ratio, minimum variance, and risk parity) for the core listed real estate portfolio and test two tactical allocation methods (i.e., volatility-based and net asset value-based) to alter the core allocations. Finally, we examine whether tactical allocation affects the benefits of including listed real estate in a mixed-asset portfolio also containing stocks and bonds.

Our results show that volatility shocks are synchronous across listed real estate sectors and countries, albeit with differences in magnitude. Overall, the global financial crisis high-volatility regime lasts longer than that of the COVID-19 pandemic. The residential and industrial sectors show the highest conditional daily volatility during the global financial crisis, while other sectors are less affected. During the COVID-19 crisis, the volatility of retail is the highest, while the residential sector is the most resilient. The sharp reaction of retail listed real estate can be explained by the mandatory shop closures and reduction in footfall traffic experienced during the pandemic. Finally, the recent rise in inflation has led to increased levels of volatility for all sectors, although to a lesser extent than during the two previous crises. All countries but Germany experience higher volatility during the COVID-19 pandemic than during the global financial crisis. The contrasting result for Germany is due to the country's high market share of residential listed real estate, which was affected by the GFC but less so by the pandemic.

When allocating to sectors, our results indicate that implementing tactical rebalancing is beneficial for strategic allocation schemes that have relatively stable and well-balanced allocations (i.e., equally-weighted, capitalization-weighted, and risk parity). For those schemes, the added flexibility provided by rebalancing makes it possible to seize opportunities that arise in high volatility or low price to net asset value regimes. However, when allocating across countries, it has a detrimental effect on listed real estate portfolio performance. This can be explained by the fact that the allocations are shifted away from Switzerland towards Germany, the U.K., and France which performed worse during the period. Tactical rebalancing leads to higher allocations to listed real estate in a mixed-asset portfolio when sectors are considered, while the opposite is true for countries. Overall, the allocation to listed real estate ranges from 4% to 26% when sectors are considered, while it is slightly higher for countries. It is the highest for strategies that are more dynamic and allow for more concentrated positions in sectors/countries.

Our results demonstrate the usefulness for investors of considering publicly available information (i.e., price volatilities and premia/discounts to NAV) when allocating funds to European listed real estate. This is especially the case for investors relying on stable and well-balanced portfolio allocation strategies, like most institutional investors.

Content table

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1. Introduction

During the past 20 years, European listed real estate (LRE) experienced three bear markets: the global financial crisis (GFC) and its aftermath leading to the European sovereign debt crisis, the COVID-19 pandemic, and the Ukraine conflict and subsequent periods of increasing inflation. European LRE prices decreased by 78% from their maximum to their minimum during the GFC, while the following debt crisis prevented market prices to recover to the 2007 peak by the end of 2012. Prices decreased by 24% and 32% during the initial phases of the COVID-19 pandemic and the Ukraine conflict, respectively.

The reaction of LRE during periods of distress has been discussed in several studies. Those have focused on the linkages between the LRE and stock markets, but also the contagion across international LRE markets (Hoesli and Reka, 2013; Liow and Huang, 2018; Milcheva and Zhu, 2018; Huang et al., 2021). Studies also show that LRE sectors react differently in periods of distress. During the GFC, industrial and retail LRE experienced higher volatility compared to apartments and self-storage properties in the U.S. (S&P Dow Jones Indices, 2020). For the COVID-19 crisis, Hoesli and Malle (2022) report that retail and hospitality properties were affected the most, while the residential and industrial sectors were less affected.

Large price fluctuations are a major concern for investors. These have a disproportionate impact on volatility which is a central consideration when deriving a portfolio's strategic asset allocation (SAA). It is also important to understand how these large price movements vary across LRE sectors and/or countries as this permits to assess portfolio downside risk more accurately. Going beyond strategic allocation, volatilities and deviations from net asset value (NAV) may be used as inputs to devise tactical asset allocation (TAA) strategies for liquid asset classes. The sharp reaction of some LRE sectors to unforeseen events suggests that volatility spikes may provide entry points at favorable price levels that could be exploited for TAA (Liu and Lu, 2020; Demiralay and Kilincarslan, 2022). Given that deviations from NAV have been shown to be mean reverting (Patel et al., 2009; Schiller et al., 2022), a price decline relative to NAV could also constitute an attractive price level (Letdin et al., 2022).

Our paper analyzes how the volatility of European LRE across sectors and countries has changed during the period 2003-2022. We also study how this information, as well as deviations from NAV, can be used in a dynamic portfolio framework. Our focus is on the main sectors (diversified, industrial, office, residential, and retail) and countries (Belgium, France, Germany, Sweden, Switzerland, and the U.K.) of the listed market. The European case is interesting as NAVs are widely reported by LRE companies and are based on regular independent appraisals of their properties. Such reporting has been shown to decrease information asymmetry and increase liquidity (Ghosh et al., 2020).

To assess how the volatility of European LRE has changed over time and space, we estimate volatilities using a GARCH model and then identify volatility regimes with a Markov switching model. We then investigate the impacts of rule-based tactical rebalancing on the performance and composition of an LRE portfolio. For this, we consider five strategic allocation approaches (i.e., equally-weighted, capitalization-weighted, maximum Sharpe ratio, minimum variance, and risk parity) for the core LRE portfolio and test two tactical allocation methods (i.e., volatility- and NAV-based) to alter the core allocations. Finally, we examine whether tactical allocation affects the allocation to LRE in a mixed-asset portfolio containing stocks and bonds.

Our results show that volatility shocks are synchronous across LRE sectors and countries, albeit with differences in magnitude. Overall, the GFC high-volatility regime lasts longer than that of the COVID-19 pandemic. The residential and industrial sectors show the highest conditional daily volatility during the GFC, while other sectors are less affected. During the COVID-19 crisis, the volatility of retail is the highest, while residential LRE is the most resilient sector. Finally, the recent rise in inflation has led to increased levels of volatility for all LRE sectors except the retail sector. All countries but Germany experience higher volatility during the COVID-19 pandemic than during the GFC.

When allocating to sectors, our results indicate that implementing TAA is beneficial for strategic allocation schemes that have relatively stable and well-balanced allocations. For those schemes, the added flexibility provided by TAA makes it possible to seize opportunities that may arise in high volatility or low price to NAV regimes. For the more dynamic strategies, incorporating TAA is inconsequential at best and detrimental at worst. However, when allocating across countries, implementing tactical rebalancing has a detrimental effect on LRE portfolio performance. This can be explained by the fact that TAA shifts the allocation away from Switzerland towards worse performing countries (Germany, the U.K., and France). Tactical rebalancing leads to higher allocations to listed real estate in a mixed-asset portfolio when sectors are considered, while the opposite is true for countries. Overall, the allocation to LRE ranges from 4% to 26% when sectors are considered, while it is slightly higher for countries. It is the highest for strategies that are more dynamic and allow for more concentrated positions in sectors/countries.

The paper contributes to the literature in several ways. First, our results provide evidence regarding the time-varying nature of European LRE volatilities across sectors and countries, over several bear markets. Our second contribution is to gauge the potential of LRE by investigating whether the volatility of the public market, as well as deviations from NAV, can be exploited to generate higher risk-adjusted returns, both in a multi-sector and multi-country context. Thus, the paper informs investors about how to exploit volatility spikes and NAV departures to implement tactical rebalancing in their listed real estate portfolios. Finally, the effects of tactical rebalancing on the weight of LRE in a mixed-asset portfolio are considered. This is undertaken by using bootstrap mean-variance optimization that permits to obtain robust portfolio allocations.

The remainder of the paper is structured as follows. In section 2, we present an overview of the literature before discussing the data in section 3. Section 4 describes our methodology. The results are analyzed in section 5. A final section concludes.

2. Literature Review

Much research has concentrated on the linkages between the LRE and stock markets during periods of distress, as well as on the contagion across international LRE markets. Focusing on the Asian crisis, Kallberg et al. (2002) report that stock returns Granger cause LRE returns. Moreover, they suggest that common factors drive the volatility of both stocks and LRE. Liow and Huang (2018) observe that the local stock market acts as a main source of LRE volatility connectedness, especially during crises. Hoesli and Reka (2013) find that the spillover effects between local and global LRE are larger for the U.S. than for the U.K. and Australia. They also report evidence of contagion from the U.S. LRE market to its U.K. counterpart during the subprime crisis. Milcheva and Zhu (2018) find that the spillover risk dramatically increases during the GFC and can explain up to 60% of real estate risk. Caporin et al. (2021) report that contagion from REITs to the stock market rose during the GFC and the European sovereign debt crisis. Finally, Huang et al. (2021) suggest that it is difficult to diversify risks across global REIT markets during the post-GFC period due to the increased role of cross-country dependence.

Evidence suggests that LRE sectors react differently to crises. The GFC resulted in higher volatility of industrial and retail properties in the U.S. compared to the apartment and self-storage sectors (S&P Dow Jones Indices, 2020). During the recent pandemic, retail and residential real estate exhibited the worst performance, whereas the healthcare and technology sectors reacted positively to COVID-19 cases (Ling et al., 2020; Milcheva, 2022). In Europe, the COVID-19 crisis resulted in severe drawdowns for retail and hospitality LRE, while the residential and industrial sectors were the least affected (Hoesli and Malle, 2022). Focusing on the Ukraine conflict and defining proximity as both physical distance and political closeness, Wang et al. (2023) find that proximity to the conflict matters, but the impact of the disaster is not uniform across different property types.

Large price fluctuations are a concern for investors and hence much research has concentrated on modelling volatility. One important challenge is that returns exhibit heteroskedasticity and volatility persistence, leading to volatility clustering. The Autoregressive Conditional Heteroskedasticity (ARCH) model (Engle, 1982) and its refinements have been proposed to deal with this issue. Bollerslev (1986) provides a major improvement by introducing the Generalized ARCH (GARCH) which allows for a more flexible lag structure. Although higher order GARCH specifications can be used, GARCH(1,1) is widely applied and usually sufficient to deal with cases encountered in practice (Bollerslev et al., 1992; Engle, 2001; Hansen and Lunde, 2005). For U.S. REITs, this is confirmed by the evidence reported in Asteriou and Begiazi (2013).

GARCH models have been widely applied for estimating the volatility of U.S. listed real estate, with fewer applications for European and Asian markets. Stevenson (2002) examines whether the volatilities of equity and fixed income markets influence the volatility of U.S. REITs. He finds that the volatilities of small cap and value stocks have the greatest impact on REIT volatility. Focusing on the effects of data frequency, Cotter and Stevenson (2006) report that the linkages both within the U.S. REIT sector and between REITs and value stocks are weaker when daily rather than monthly data are used (see also Cotter and Stevenson, 2007). Lee et al. (2018) examine the linkages between the volatility of real estate securities and macroeconomic risk in 11 markets and find that volatility is strongly positively related to most of their macroeconomic risk factors. Liow (2013) studies volatility spillovers across several European markets and finds that they increase from 1999 to 2002. Akimov et al. (2019) also examine European LRE markets and show that both returns and volatilities are sensitive to interest rate changes.

Understanding how volatility behaves is critical for portfolio allocation. Considering four sectors of the Japanese REIT market, Razak (2023) concludes that portfolios with REITs have higher risk-adjusted returns compared to portfolios of stocks and bonds only. Sa-Aadu et al. (2010) find that U.S. REITs are effective in hedging a portfolio against the volatility shocks of consumption growth. Huang and Zhong (2013) report that the diversification benefits of REITs are time-varying and that investors should invest in REITs but reduce their positions during crises. Similarly, Abuzayed et al. (2020) find that diversification benefits of REITs during crises are small due to their strong correlation with stocks and high transaction costs resulting from the need to rebalance the portfolio on a regular basis. Newell and Marzuki (2016) conclude that U.K. REITs improve the performance of a mixed-asset portfolio during the post-GFC period. Considering eight countries, Peng and Schulz (2013) use a time-varying covariance matrix model for a mixed-asset portfolio and show that REITs are useful for investors following a buy-and-hold strategy.

Concerning the optimal allocation to LRE in a mixed-asset portfolio, Lee and Stevenson (2005) conclude that LRE's weight should be between 10 and 18% for the U.S. Focusing on Europe, the average allocation to LRE is about 20% when considering uncertainty aversion (Lizieri et al., 2022). The evidence also suggests that the benefits of holding LRE increase with the time horizon. For instance, MacKinnon and Al Zaman (2009), using U.S. data, find that the allocation to LRE increases from 8% to 20% as the horizon increases. This can be explained by the fact that, over a mid- to long-term horizon, LRE becomes more akin to direct real estate (Hoesli and Oikarinen, 2012 and 2021).

Real estate portfolio diversification across geographies and/or sectors has also been widely examined. International diversification strategies have been shown to outperform sectoral diversification strategies for direct real estate (Eichholtz et al., 1995; Candelon et al., 2021). In the context of REITs, Deng et al. (2018) find that it is beneficial to diversify real estate portfolios internationally, although those are more affected by tail dependences than mixed-asset portfolios. Ciochetti et al. (2015) conclude that REIT diversification across countries can lower the risk of a portfolio to the extent that the economies of the areas are independent of each other.

Some research on the price behavior of LRE suggests that a dynamic allocation approach might be useful. For the U.S., positive returns can be generated with momentum strategies in the short run, whereas trend reversal strategies are applicable in the long run (Liu and Lu, 2020; Chen et al., 2022). A combination of REIT sectors with trend following overlays outperforms a passive benchmark on a risk-adjusted basis, across five regions/countries (Moss et al., 2017). Demiralay and Kilincarslan (2022) use a Markov regime switching model and find that uncertainty measures are regime dependent and vary across U.S. REIT sectors. This suggests that it would be beneficial to alter sectoral expositions based on market conditions. Finally, Letdin et al. (2022) show that a long-short strategy that purchases (sells short) U.S. REITs with the lowest (highest) NAV premium generates 6% per year.

3. Data

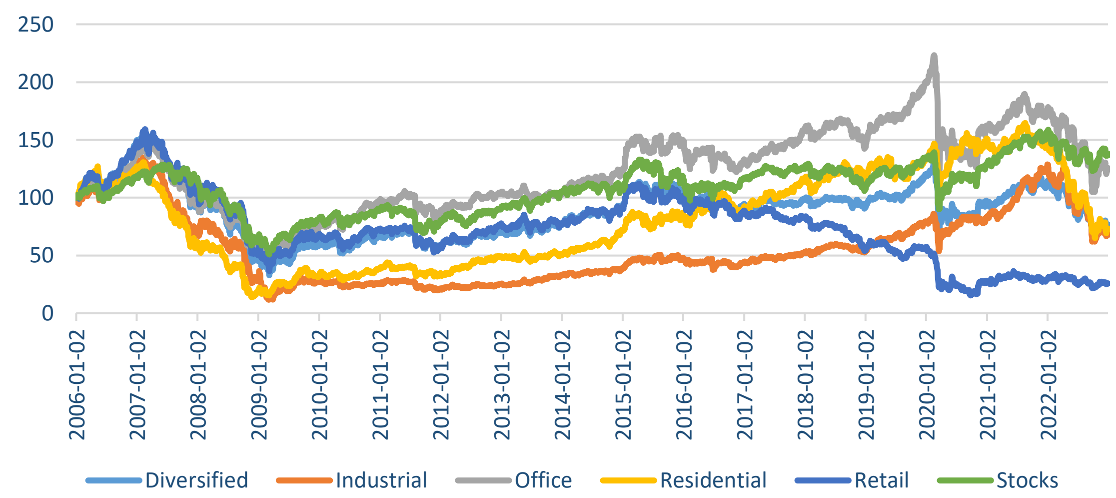
Data were gathered for the five main LRE sectors in Europe (i.e., diversified, industrial, office, residential, and retail) and the six largest LRE markets (i.e., Belgium, France, Germany, Sweden, Switzerland, and the U.K.). We use daily data from the beginning of 2006 to the end of 2022 for sectors (2003-2022 for countries). The length and scope of the time series were determined by the availability of LRE data and importance of these sectors/countries based on market capitalization.

We measure LRE returns by using the FTSE EPRA/NAREIT Developed Europe sector indices as well as the FTSE EPRA/NAREIT indices for the six countries considered, sourced from the European Public Real Estate Association (EPRA). Monthly premium/discount to NAV data and market capitalizations are also from EPRA. Stock price and total return indices, as well as government and corporate bond total return indices are collected from the Refinitiv Eikon and Bloomberg databases. Specifically, these are the STOXX Europe 600 Gross Total and Price Return indices, the Bloomberg EU Govt All Bonds Total Return index, and the Bloomberg Euro-Aggregate Greater Europe Corporate Total Return Unhedged index. All data are in euros.

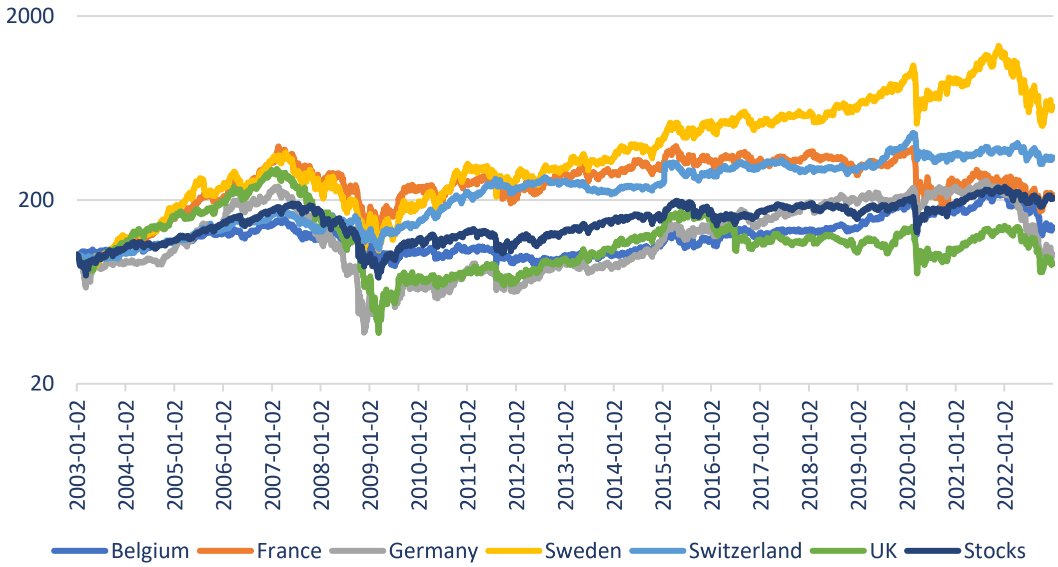
Panel A of Figure 1 presents price return indices of LRE sectors and stocks, while Panel B displays LRE indices for countries and stocks. The majority of LRE sectors have similar movements to those of stocks during the GFC and Ukraine conflict periods. In contrast, the behavior of LRE across sectors was more contrasted during the COVID-19 crisis. As discussed in previous research (Hoesli and Malle, 2022), retail exhibited the worst performance during the COVID-19 pandemic, because of strict quarantine measures and the related increase in e-commerce. Offices were also severely impacted by the pandemic and the shift to remote work. Many sectors, in particular the retail sector, experienced a price erosion. This is largely because the sample period starts just before the GFC when prices were high. The poor performance of the retail sector is also due to the secular decline of bricks-and-mortar retail that happened over the later period of our sample. Indices of LRE across countries comove with stocks during the GFC period. Sweden shows the largest cumulative price return, while the U.K. experiences the lowest return, with a noticeable drop in 2016 due to the Brexit referendum. Overall, we observe fewer differences across countries than across sectors.

Figure 1.

Panel A. Price return indices for LRE sectors and stocks, 2006-2022



Panel B. Price return indices for LRE countries and stocks, 2003-2022



Sources: EPRA, Refinitiv Eikon and authors' calculations.

Table 1 shows summary statistics for European LRE sectors, stocks, government bonds and corporate bonds. The sample consists of 4,360 daily observations for 2006-2022. Stocks deliver the highest average return (7.01%), followed by office (6.78%), industrial (5.83%) and diversified LRE (4.79%). The average total return on retail is only 0.73%, highlighting that the income return was able to more than compensate for price declines. As expected, government and corporate bonds have the lowest average returns (except for retail) at 2.27% and 2.19%, respectively, and are also the least risky assets. Stocks have the highest Sharpe ratio (0.16), followed by offices (0.14). Given that the sample period starts just prior to the pre-GFC peak, the Sharpe ratio is negative for other LRE sectors.[1] The correlations between LRE sectors and stocks range from 0.63 (industrial and residential) to 0.78 (diversified). Both government and corporate bonds are either lowly positively or negatively correlated with LRE.

Industrial and residential LRE experienced their lowest and highest daily returns during the GFC. In contrast, office, retail and diversified companies, as well as government and corporate bonds, all experienced minimum and maximum returns during the COVID-19 pandemic. Stocks had their lowest return during COVID-19, while the highest return was during the GFC. The extreme values can be linked to specific events. For example, the lowest stock return occurred on March 12, 2020. This was a response to the COVID-19 pandemic declaration by the World Health Organization a day before. Conversely, on November 9, 2020, the market experienced a sharp increase as a response to Pfizer's promising results in the COVID-19 vaccine testing announced on that morning. Considering the shape of the return distribution, all assets exhibit negative skewness except retail LRE. The positive excess kurtosis indicates that all series have much fatter tails than the normal distribution.

Table 2 shows summary statistics for LRE by country, stocks, government bonds and corporate bonds. The sample consists of 5,203 daily observations for 2003-2022. Sweden delivers the highest average total return (16.76%), followed by France (11.56%), Switzerland (10.41%), Belgium (8.83%) and the stock market (8.54%). Government and corporate bonds have the lowest average returns. Overall, Switzerland is the best performing country with a Sharpe ratio of 0.50, followed by Sweden (0.39), Belgium (0.29), France (0.26) and stocks (0.24). Germany and the U.K. exhibit the lowest Sharpe ratios (0.03 and 0.01, respectively). The correlations between individual countries and stocks range from 0.37 (Switzerland) to 0.69 (the U.K.) and are lower than those between LRE sectors and stocks.

[1] Appendix 1 reports summary statistics for a period starting after the GFC and European sovereign debt crisis (i.e., for 2013-2022).

Table 1. Summary statistics of total returns for LRE sectors, stocks and bonds, 2006-2022

	Diversified	Industrial	Office	Residential	Retail	Stocks	Govt. Bonds	Corp. Bonds
Avg. Return (ann.)	4.79%	5.83%	6.78%	4.04%	0.73%	7.01%	2.27%	2.19%
Geo. Avg. Ret.(ann.)	-0.07%	1.75%	4.92%	0.60%	-3.47%	5.31%	2.20%	2.17%
Max. Return (daily)	8.38%	17.29%	11.74%	19.00%	22.57%	9.87%	1.88%	1.06%
Min. Return (daily)	-11.65%	-18.28%	-12.45%	-16.68%	-18.26%	-11.47%	-1.69%	-2.15%
St. Deviation (ann.)	22.13%	28.53%	19.82%	26.21%	29.25%	19.13%	4.40%	2.90%
Sharpe Ratio	-0.10	-0.02	0.14	-0.06	-0.19	0.16	0.00	-0.01
Skewness	-0.39	-0.35	-0.23	-0.13	0.50	-0.29	-0.05	-0.90
Kurtosis	9.50	14.98	13.49	17.08	18.97	11.62	7.29	12.56
Value-at-Risk (95%)	-38.18%	-48.17%	-32.22%	-53.02%	-50.62%	-25.73%	-5.50%	-5.03%
Max. Drawdown	-77.24%	-90.29%	-66.75%	-88.87%	-81.04%	-58.37%	-21.90%	-17.72%
Nb. of Observations	4,360	4,360	4,360	4,360	4,360	4,360	4,360	4,360
Nb. of Years	17	17	17	17	17	17	17	17

Correlations	Diversified	Industrial	Office	Residential	Retail	Stocks	Govt. Bonds	Corp. Bonds
Diversified	1.00							
Industrial	0.80	1.00						
Office	0.90	0.73	1.00					
Residential	0.72	0.62	0.71	1.00				
Retail	0.82	0.63	0.79	0.57	1.00			
Stocks	0.78	0.63	0.71	0.63	0.68	1.00		
Govt. Bonds	0.00	0.01	0.06	0.05	-0.01	-0.09	1.00	
Corp. Bonds	0.06	0.06	0.14	0.06	0.04	-0.05	0.74	1.00

Note: red stands for weak/negative correlation, yellow for moderate correlation (50th percentile), and green for strong correlation.

Sources: EPRA, Refinitiv Eikon, Bloomberg and authors' calculations.

Table 2. Summary statistics of total returns for LRE by country, stocks and bonds, 2003-2022

	Belgium	France	Germany	Sweden	Switzerland	U.K.	Stocks	Govt. Bonds	Corp. Bonds
Avg. Return (ann.)	8.83%	11.56%	6.36%	16.76%	10.41%	6.01%	8.54%	2.71%	2.74%
Geo. Avg. Ret (ann.).	7.61%	8.98%	3.40%	13.68%	9.84%	2.89%	7.06%	2.66%	2.73%
Max. Return (daily)	11.01%	18.61%	14.78%	12.20%	12.25%	11.51%	9.87%	1.88%	1.06%
Min. Return (daily)	-11.42%	-14.71%	-9.47%	-15.59%	-7.49%	-19.26%	-11.47%	-1.69%	-2.15%
St. Deviation (ann)	17.25%	24.40%	24.54%	28.01%	14.34%	25.03%	18.51%	4.29%	2.89%
Sharpe Ratio	0.29	0.26	0.03	0.39	0.50	0.01	0.24	0.00	0.03
Skewness	-0.19	0.53	0.10	-0.15	0.38	-0.49	-0.28	-0.09	-0.87
Kurtosis	14.82	17.46	10.66	8.64	16.12	14.02	11.85	7.28	11.52
Value-at-Risk (95%)	-13.9%	-29.8%	-47.9%	-34.3%	-9.5%	-45.2%	-22.3%	-3.8%	-4.3%
Max. Drawdown	-39.8%	-64.6%	-82.8%	-68.1%	-34.6%	-86.1%	-58.4%	-21.9%	-17.9%
Nb. of Observations	5,203	5,203	5,203	5,203	5,203	5,203	5,203	5,203	5,203
Nb. of Years	20	20	20	20	20	20	20	20	20

Correlations	Belgium	France	Germany	Sweden	Switzerland	U.K.	Stocks	Govt. Bonds	Corp. Bonds
Belgium	1.00								
France	0.66	1.00							
Germany	0.65	0.64	1.00						
Sweden	0.65	0.66	0.67	1.00					
Switzerland	0.45	0.47	0.47	0.49	1.00				
U.K.	0.59	0.69	0.58	0.62	0.44	1.00			
Stocks	0.54	0.65	0.61	0.66	0.37	0.69	1.00		
Govt. Bonds	0.07	0.03	0.04	0.04	0.12	-0.03	-0.12	1.00	
Corp. Bonds	0.10	0.06	0.05	0.07	0.18	0.03	-0.08	0.77	1.00

Note: red stands for weak/negative correlation, yellow for moderate correlation (50th percentile), and green for strong correlation.

Sources: EPRA, Refinitiv Eikon, Bloomberg and authors' calculations.

4. Methodology

4.1. Time-Varying Volatility of Listed Real Estate Returns

The first part of the analysis focuses on the time-varying behavior of the daily volatility of LRE price returns in Europe. This is done both for sectors and countries. For each time series, we estimate a model that captures both the conditional mean of the time series and its conditional volatility. The mean process of our time series is estimated using the autoregressive moving average (ARMA) part of the model:

$$\mu_t = \delta + \sum_{m=1}^{p} \phi_m Ret_{t-m} + \sum_{n=1}^{q} \theta_n \varepsilon_{t-n} + \varepsilon_t \quad (1)$$

where μ_t is the conditional mean at time t, Ret_{t-m} is the return lagged by m periods (i.e., autoregressive term), ε_{t-n} is the error term lagged by n periods (i.e., moving average term), and δ, ϕ_m and θ_n are coefficients to be estimated (for the intercept, autoregressive term at lag m and moving average term at lag n, respectively). The numbers of lags for the AR (p) and MA (q) parts of the mean model are determined using the autocorrelation function (ACF) and partial autocorrelation function (PACF) of logarithmic returns.[2] The conditional time-varying volatility is estimated using a GARCH(1,1) model:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

where σ_t^2 is the conditional volatility in t, ε_{t-1}^2 is the squared error term in $t-1$, σ_{t-1}^2 is the squared conditional volatility term in $t-1$, and ω, α and β are coefficients to be estimated (for the intercept, squared error and squared conditional volatility terms, respectively). To ensure the condition of positive volatility estimates, we restrict $|\phi| < 1$, $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. For stationarity, we also need to restrict $\alpha + \beta < 1$. We estimate simultaneously the ARMA(p,q)-GARCH(1,1) models using a maximum likelihood method. Finally, we analyze the residuals to verify if the model assumptions are met.

We then identify high and low volatility regimes by applying a Markov regime switching model (Hamilton, 1989) to the estimated volatility time series. This is useful to model time series that transition over a finite set of regimes with distinct statistical characteristics. Transitions between regimes follow a random Markov process, where the probability of transitioning depends only on the regime in the previous period. Our model is:

$$y_t = \mu_{s_t} + \varepsilon_{s_t} \quad (3)$$

with:

$$\varepsilon_{s_t} \sim iid\ N(0, \sigma_s^2)$$

$$P(s_t = i \mid s_{t-1} = j) = P_{ij} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}$$

where y_t is the estimated volatility at time t, μ_{s_t} is the regime-specific mean for the state variable s at time t, ε_{s_t} is the error term at time t for the state variable s, σ_s^2 is the variance of the error term for the state variable s, and P_{ij} is the probability of transitioning from regime j at time $t-1$ to regime i at time t. As we aim to identify two volatility regimes (i.e., high versus low), our model incorporates two states that may have different mean and variance levels.

[2] Based on the error terms of the ARMA model, we performed an Engle's ARCH test that confirmed persistence in the volatilities of all return series and, hence, the need for GARCH models.

4.2. Real Estate Portfolio Analysis

In this part, the objective is to investigate whether price volatility and deviations from NAV can be used in a tactical allocation scheme to generate superior risk-adjusted returns relative to strategic allocation strategies that do not allow for tactical rebalancing. This is done for an investor diversifying either across property sectors or across countries. We backtest allocation strategies with and without tactical rebalancing, and assess how portfolio risk and return characteristics change when tactical allocation is implemented. We use a realistic investment setting with portfolio rebalancing and transaction costs, and that avoids look-ahead bias (Appendix 2 illustrates our backtesting procedure). We consider five strategic allocation strategies: equally-weighted, capitalization-weighted, maximum Sharpe ratio, minimum variance, and risk parity (Moss et al., 2017; Hoesli et al., 2023).

While the first two allocation approaches are passive in nature, the other three approaches seek to improve the portfolio expected risk-return tradeoff by incorporating the sector (country) risk and return characteristics into the portfolio construction process. The maximum Sharpe ratio and the minimum variance approaches rely on optimization to derive portfolio allocations. The optimal portfolios are found using a random search method that samples 100,000 potential solutions in our multi-dimensional search space (i.e., five dimensions for sectors and six for countries). This approach is favored for its relative simplicity to solve optimization problems with few dimensions (i.e., no dimensionality curse). Both the optimizations and the estimation of the risk parity allocations are based on a 256-day sample period, which corresponds to the average number of trading days per year.

The maximum Sharpe ratio approach searches for the portfolio that has the highest Sharpe ratio over the estimation period:

$$\max_{w} SR_{p,w} = \max_{w} \frac{R_{p,w} - R_f}{\sigma_{p,w}} \qquad (4)$$

subject to:

$$\sum_{i=1}^{N} w_i = 1$$

$$w_i \geq 0 \quad \forall\, i$$

with:

$$R_{p,w} = w'R$$

$$\sigma_{p,w} = w'\Sigma w$$

where $SR_{p,w}$ is the Sharpe ratio of portfolio p with sector (country) weights w, $R_{p,w}$ is the return of portfolio p with sector (country) weights w computed using the vector of sector (country) returns R, $\sigma_{p,w}$ is the standard deviation of portfolio p with sector (country) weights w derived using the sector (country) returns covariance matrix Σ, R_f is the risk-free rate and N is the number of sectors (countries) considered.

The minimum variance optimization is expressed as:

$$\min_{w} \sigma_{p,w} \qquad (5)$$

subject to:

$$\sum_{i=1}^{N} w_i = 1$$

$$w_i \geq 0 \quad \forall\, i$$

with:

$$\sigma_{p,w} = w' \Sigma w$$

where $\sigma_{p,w}$ is the standard deviation of portfolio p with sector (country) weights w derived using the sector (country) returns covariance matrix Σ and where N is the number of sectors (countries) considered.

Finally, the risk parity approach derives portfolio weights such as each sector (country) contributes equally to the portfolio risk (defined as standard deviation):

$$\sigma_i = \sigma_j \quad \forall\, i \text{ and } j \tag{6}$$

or equivalently:

$$\sigma_i = \frac{\sigma_{p,w}}{N} \quad \forall\, i$$

where $\sigma_{i,w}$ ($\sigma_{j,w}$) is the standard deviation of sector (country) i (j, respectively), $\sigma_{p,w}$ is the standard deviation of portfolio p with sector (country) weights w derived using the sector (country) returns covariance matrix Σ and where N is the number of sectors (countries) considered.

For each of the five strategies, we assess the benefits which result from allowing for a 20% tactical allocation. The tactical pocket is re-allocated based on two rules: (1) a volatility-based approach which allocates to sectors (countries) with recent high volatility and (2) an NAV-based approach which is exposed to sectors (countries) with high discount to NAV (or low premium to NAV). The underlying assumption is that LRE overreacts to major unexpected events and, hence, a period of high volatility should be followed by a period of high returns (Liu and Lu, 2020; Chen et al., 2022). These trend reversal tactical rules are designed to expose the portfolio to potential market rebounds. Under normal market conditions, the tactical allocation pocket will be invested similarly to the rest of the portfolio.

The volatility-based TAA approach uses the estimated volatility estimates as inputs. Hence, the first step is to estimate the volatility time series for each sector (country) with a GARCH(1,1) model. Each volatility time series is then used as an input into a two-regime Markov switching model that allows for switching coefficients for both the level and the standard error of the fitted series. This permits us to determine if a given sector (country) is currently in a high or low volatility regime. As the GARCH model is estimated over the previous 256 days, the volatility regimes are identified only with data known at the time of the TAA. If one or more sectors (countries) are in a high volatility regime, the 20% TAA pocket will be allocated to these sectors (countries) as follows:

$$w_i = \frac{\sigma_i}{\sum_{j=1}^{N^*} \sigma_j} \tag{7}$$

where w_i is the weight allocated to sector (country) i which is in a high volatility regime, σ_i is the current estimate of volatility for sector (country) i based on the GARCH(1,1) model, and $\sum_{j=1}^{N^*} \sigma_j$ is the sum of the current volatility estimates for the N^* sectors (countries) which are in a high volatility regime.

The NAV-based TAA approach uses the time series of premia/discounts to NAV for each sector (country) as inputs into a two-regime Markov switching model fitted over the previous 256 observations. This permits us to determine if a sector (country) is currently in a high or low premium/discount to NAV regime. The TAA pocket is allocated equally across sectors (countries) that are experiencing a low premium/discount to NAV regime, if any. A low premium/discount to NAV regime does not necessarily imply that the sector (country) is currently trading at a discount to its NAV. Indeed, a sector (country) can trade at a premium to NAV that is low by historical standards and, hence, be classified as being in a low premium/discount to NAV state. Both TAA approaches allow for tactical allocations that last for up to 12 months and that will be liquidated earlier if their total return is above 50% (i.e., profit-taking level) or below -10% (i.e., stop-loss level). To check the robustness of our results, we also consider TAA durations of 6 and 18 months, profit-taking levels of 25% and 100%, and stop-loss levels of -5% and -20%, respectively.

We backtest these investment strategies with a daily frequency over the period from 2007 to 2022 for sectors (2004 to 2022 for countries). The strategic asset allocation is rebalanced every month, and dividends are reinvested only at the time of rebalancing. Hence, performance accounts for the cash drag resulting from the time necessary to invest dividends. The tactical asset allocation is also monitored monthly for potential trigger events (i.e., TAA inception and TAA liquidation due to TAA duration, profit taking, or stop loss). The TAA pocket is not rebalanced and, hence, the tactical allocation is a simple buy-and-hold strategy until liquidation. We consider transaction costs of 10 basis points (bps), which correspond to the typical trading fees for exchange-traded funds that track an equity index.

For both sectors and countries and for each of the five allocation strategies, the above procedure generates three time series of returns: (1) without tactical rebalancing, (2) with volatility-based TAA, and (3) with NAV-based TAA. We then test whether the implementation of tactical rebalancing schemes leads to an improvement of the LRE portfolio's Sharpe ratio. We also consider how the rebalancing schemes impact value-at-risk (VaR) and maximum drawdown. Finally, the changes in portfolio allocations across sectors (countries) are analyzed.

4.3. Mixed-Asset Portfolio Analysis

In the last part of the analysis, we assess the optimal allocation to LRE in a mixed-asset portfolio containing stocks, government bonds, and corporate bonds. We seek to answer two questions: (1) What is the optimal allocation to LRE when various asset allocation strategies are considered? (2) Does the inclusion of the tactical LRE pocket change the optimal allocation to LRE? For both the sector and country analyses, we derive efficient frontiers without and with LRE, and by considering separately each of the 15 LRE strategies (i.e., 5 strategies x 3 TAA setups).

We rely on bootstrapped portfolio optimization to obtain robust allocations (Srivatsa et al., 2010). More specifically, we use an approach inspired by the resampled efficiency method proposed by Michaud and Michaud (2008), but substitute the parametric bootstrap by a non-parametric block bootstrap. This is motivated by the fact that the resampled efficiency method assumes that returns are normally distributed and serially independent. However, our return series do not meet these assumptions, as indicated by the results of the Jarque-Bera tests and the autocorrelation functions (the latter are discussed in section 4).[3]

We derive efficient frontiers using a four-step procedure: (1) simulate asset returns by bootstrapping b blocks consisting of 500 consecutive days of returns for our four asset classes; (2) estimate the expected return vector and the covariance matrix of the simulated asset returns (i.e., of the block bootstrapped sample); (3) derive the efficient frontier by running mean-variance optimizations using the parameters estimated over the bootstrapped sample; and (4) repeat 10,000 times steps 1 to 3 and average the optimal weights for each point on the efficient frontiers. Note that each block is a 500 x 4

[3] The Jarque-Bera test is a goodness-of-fit test of whether the skewness and the excess kurtosis of the sample data are jointly zero. The test statistic is $JB = \frac{n}{6}\left[S^2 + \frac{1}{4}(K-3)^2\right]$, where n, S and K are the number of observations, skewness, and kurtosis, respectively. Under the null hypothesis of normality, it is distributed asymptotically as a Chi-squared with two degrees of freedom.

matrix (i.e., the number of days x number of asset classes), hence we preserve both the return autocorrelation of each asset class and the cross-asset correlations. The length of the block is selected based on the ACF, while the number of blocks b (i.e., eight for sectors and 10 for countries) is chosen so that the bootstrapped sample is roughly the same length as the original time series. Finally, the optimization consists of minimizing the portfolio variance for a given expected return, under the constraints that the asset weights are all positive and sum to one. To obtain the efficient frontier, we perform this optimization for 50 equidistant returns ranging from the return of the minimum variance portfolio to the maximum achievable portfolio return (i.e., the return of the asset class which has the highest return in the bootstrapped sample).

5. Results

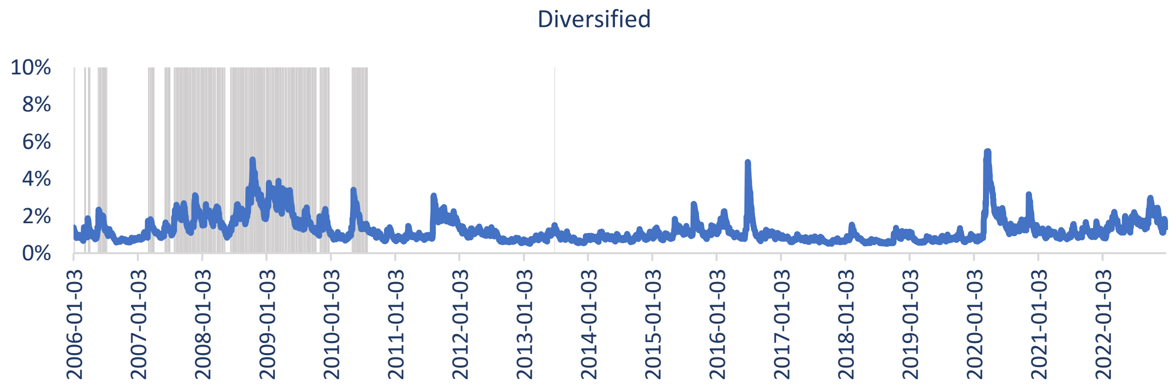
5.1. Sector Analysis

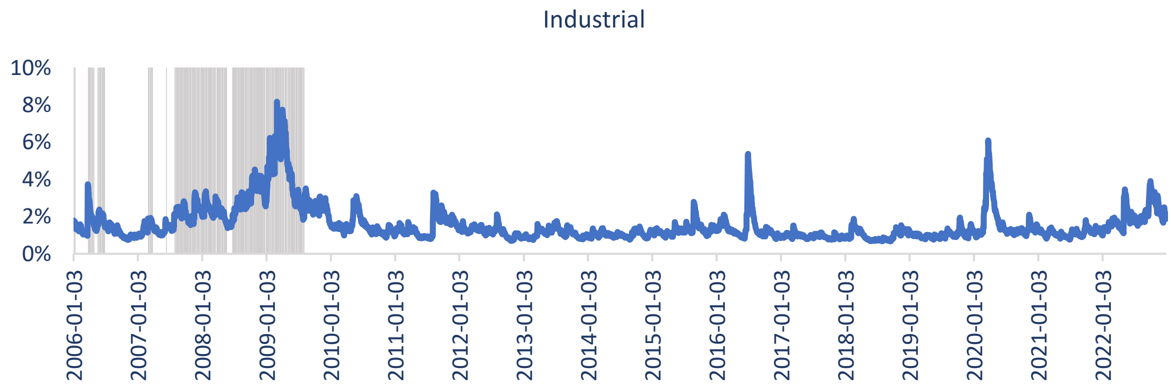
a. Time-Varying Volatility of Listed Real Estate Returns

We start our discussion of the results by considering the time-varying behavior of the daily volatilities of LRE returns. Based on the analysis of the ACFs and PACFs, we specify the ARMA-GARCH models as follows: AR(1)-GARCH(1,1) for diversified, industrial, residential, and retail LRE, AR(2)-GARCH(1,1) for offices, and AR(0)-GARCH(1,1) for stocks. Focusing on the GARCH part of the model, the coefficients for the lagged squared innovation (i.e., alpha) and the lagged squared conditional volatility (i.e., beta) are highly significant for each series (Appendix 3). The alpha (beta) coefficients are close to each other across sectors and for stocks, indicating that these assets exhibit similar short-term (long-term) volatility dynamics. The higher magnitude of the beta coefficients compared to the alpha coefficients indicates that the volatility persistence has a stronger impact on the current volatility than the previous period volatility shock.

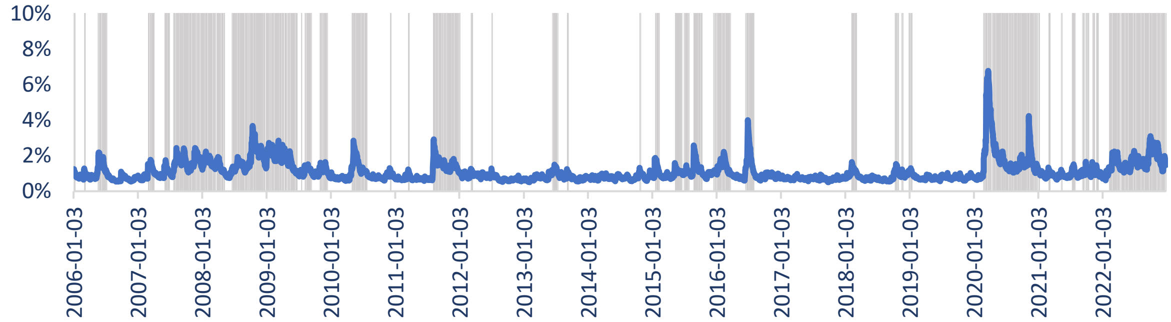
Figure 2 depicts the conditional volatility and the volatility regimes for the five LRE sectors and stocks. Overall, volatility shocks are synchronous across LRE sectors, albeit with differences in magnitude. During the GFC, the daily volatility is the highest for the residential and industrial sectors (8.60% and 8.18%, respectively), while offices (3.67%) and retail (4.46%) have volatilities that are lower than that of stocks (5.22%). In addition to variations in the economic risk of the underlying properties, those differences can result from various degrees of leverage as well as different country allocations across sectors.

Figure 2. Volatility and volatility regimes of LRE sectors and stocks

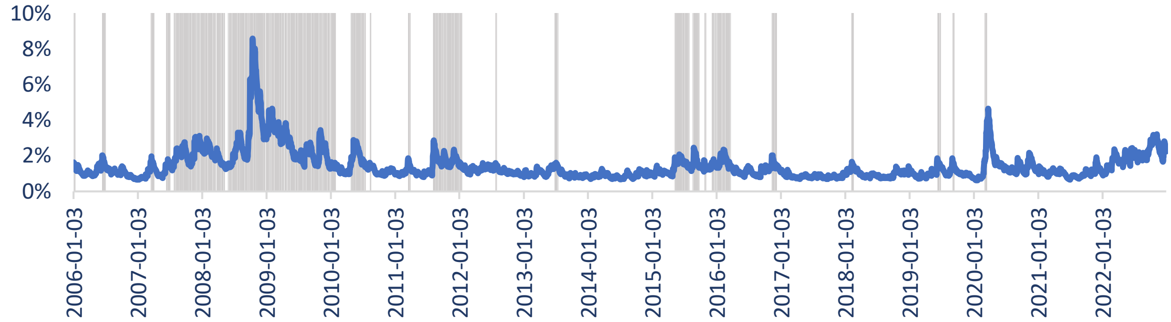




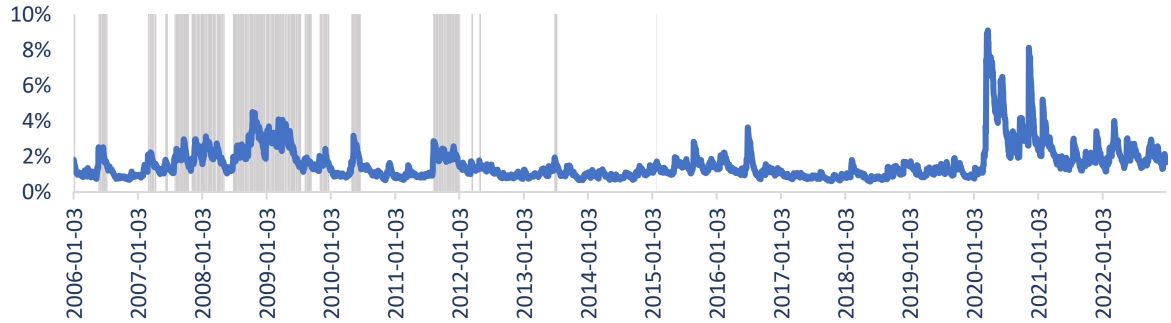
Office



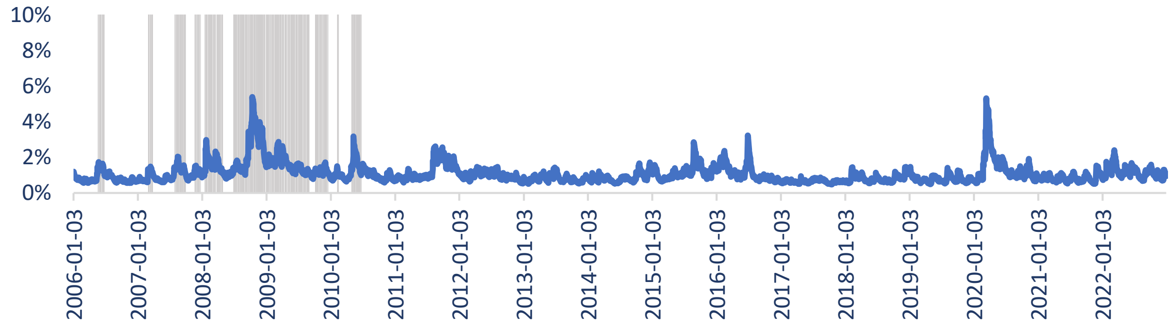
Residential



Retail



Stocks



Sources: EPRA, Refinitiv Eikon and authors' calculations.

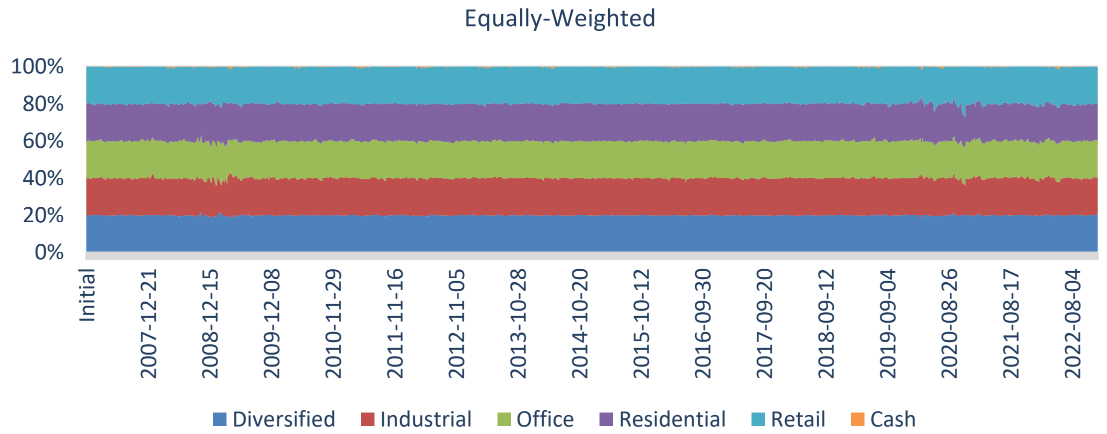
Notes: The blue line is the estimated conditional volatility. Periods of high volatility are in grey, while periods of low volatility are in white.

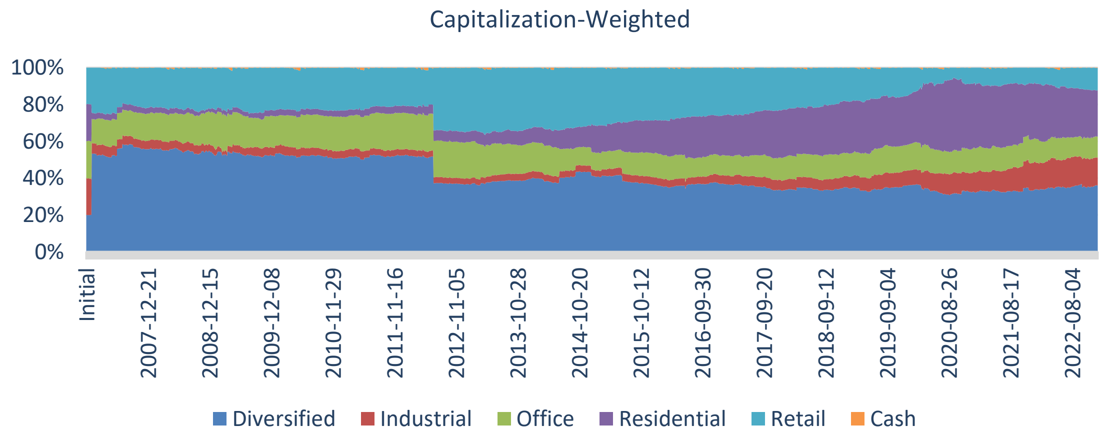
During the COVID-19 crisis, the volatility is the highest for retail (9.09%), confirming the results by Hoesli and Malle (2022). Sharp price declines for retail LRE resulted from the mandatory shop closures or reduction in footfall traffic experienced during the pandemic which further weakened the sector. The office (6.77%) and industrial (6.09%) sectors are also affected, albeit to a lesser extent. Residential LRE is the most resilient sector with a maximum volatility of 4.66%. Diversified LRE shows moderate volatility spikes both during the GFC (5.05%) and the COVID-19 pandemic (5.50%). Overall, the GFC high-volatility regime lasts longer than that of the COVID-19 pandemic. The industrial and residential sectors have higher volatilities during the GFC compared to the COVID-19 crisis, while the opposite is true for the office and retail sectors. Finally, the recent period of high inflation has led to increased levels of volatility for all LRE sectors, although to a lesser extent than during the two previous crises.

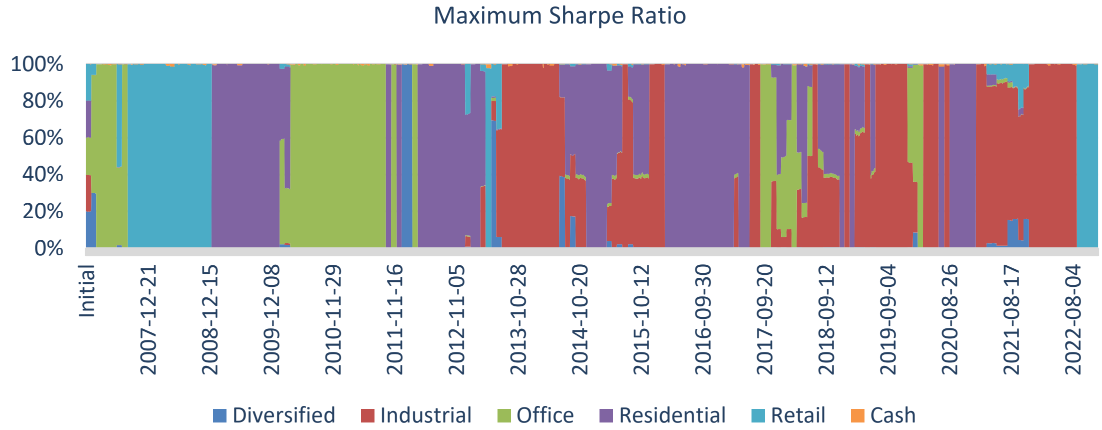
b. Real Estate Portfolio Analysis

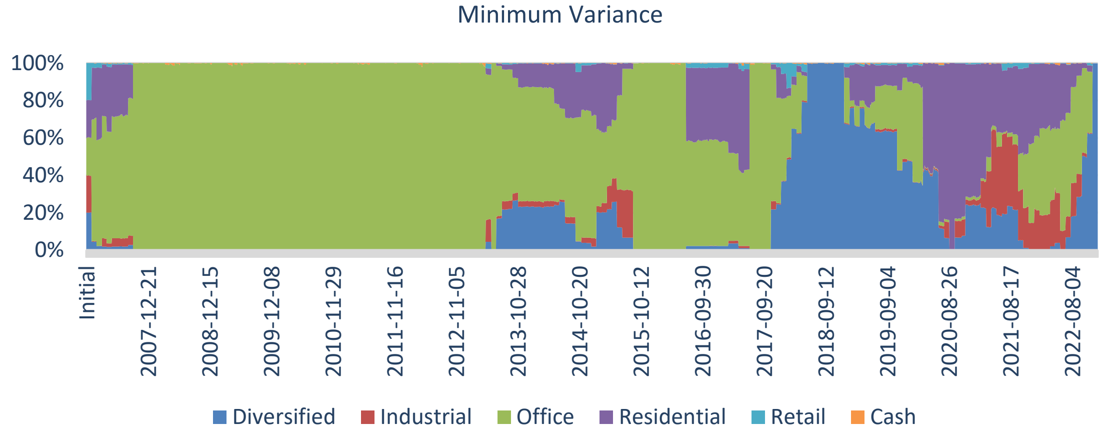
This section considers the impact of rule-based tactical rebalancing on the performance of LRE portfolios from the perspective of an investor diversifying across European LRE sectors. Figure 3 depicts the portfolio compositions over time for the five strategic asset allocation approaches when no tactical rebalancing is considered. In conjunction with the equally-weighted portfolios, the risk parity approach presents the most stable and balanced allocations over time. The capitalization-weighted approach also produces well-diversified portfolios, but with initially a larger allocation to the diversified, retail and office sectors. For this strategy, the allocations to the residential and office sectors increase materially over time, while the retail and office allocations diminish.

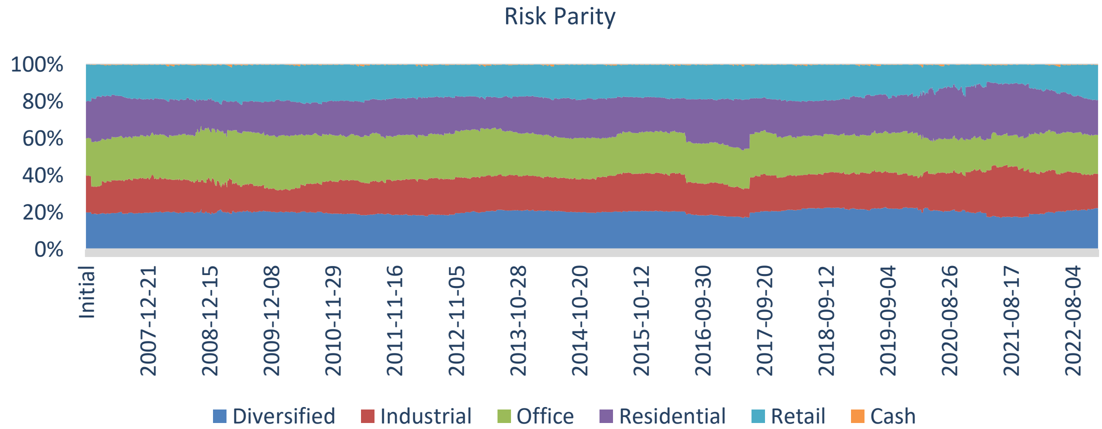
Figure 3. Strategic asset allocations (without tactical rebalancing)









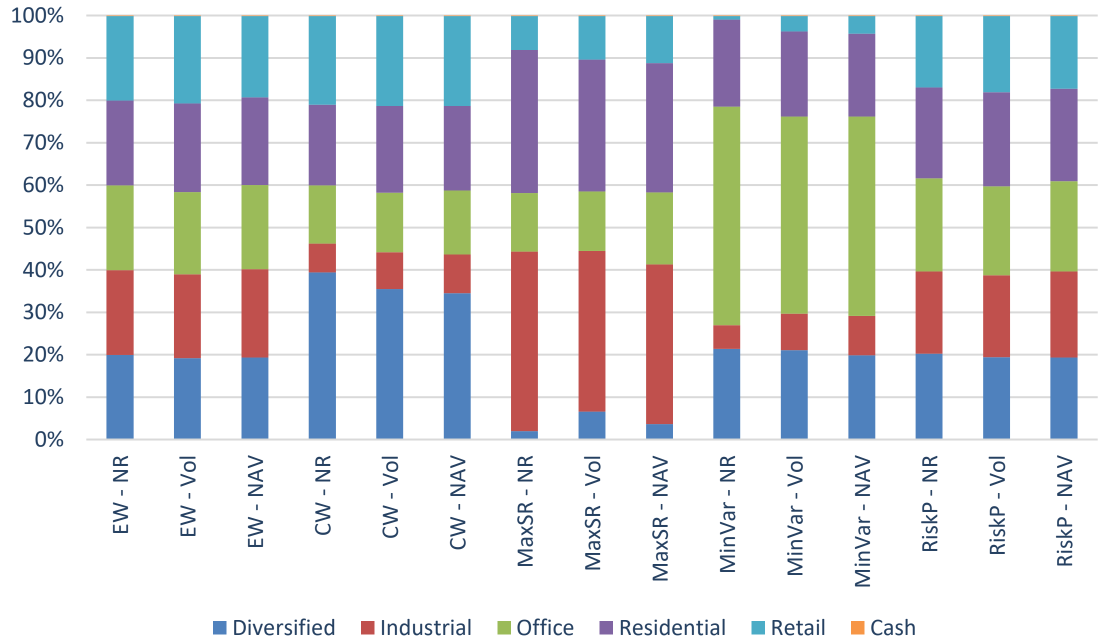


Sources: EPRA and authors' calculations.

The maximum Sharpe ratio and minimum variance approaches produce the less stable and less diversified portfolios. These portfolios are often allocated to one sector only. This is a well-known pitfall of unconstrained portfolio optimization (Hyung and de Vries, 2007). In the case of the maximum Sharpe ratio approach, no sector dominates the allocation over time. However, the minimum variance portfolios exhibit long-lasting and concentrated allocations to some sectors during certain periods. For example, the portfolios are mainly allocated to the office sector from 2007 to 2018, while the diversified sector dominates from 2018 to 2020. Over the last two years, the allocations are more balanced.

Figure 4 shows the allocations averaged over time for each of our 15 strategies (five SAA x three TAA approaches). The average allocation varies substantially across the SAA approaches, while TAAs have more muted impacts on the average allocation.[4] The equally-weighed and risk parity approaches produce well-balanced allocations, even when tactical allocation is considered. The capitalization-weighted strategies are inherently overweighted in the diversified sector, which is the largest LRE sector in Europe. For the maximum Sharpe ratio strategies, the allocations are concentrated in the industrial sector and, to a lesser extent, the residential sector, as a result of the strong performance of these sectors after the European debt crisis. Finally, the minimum variance approach is mainly allocated to offices. This is likely because the office sector was considered, until the recent turmoil, as a safe haven for real estate investors given the long maturity of office leases.

Figure 4. Portfolio compositions averaged over time for the 15 strategies



Sources: EPRA and authors' calculations.

Notes: EW = Equally-Weighted, CW = Capitalization-Weighted, MaxSR = Maximum Sharpe Ratio, MinVar = Minimum Variance, and RiskP = Risk Parity. The TAAs are denoted by NR = No Rebalancing (i.e., no TAA), Vol = Volatility-Based, and NAV = NAV-Based.

Table 3 displays the risk and return for our 15 strategies. Overall, performance metrics are dampened by the fact that the period encompasses several crises. Focusing first on performance when TAA is not implemented, the capitalization-weighted strategy has the lowest total return (-0.65%), while the maximum Sharpe ratio approach has the highest (4.92%). The latter figure is attributable to the high allocation to the well-performing industrial and residential sectors. The two strategies also exhibit the lowest (-4.45% for the capitalization-weighted method) and highest (1.52% for the maximum Sharpe ratio approach) average price returns. The higher average total return for the maximum Sharpe ratio strategy comes at the price of having the highest variance (24.0%). The minimum variance approach fulfills its role by producing the lowest variance ex post (19.3%). When adjusting returns for risk, the best performing strategy is the maximum Sharpe ratio approach (Sharpe ratio of 0.10). It is the only one which produces positive total (and price) returns, and, hence, a positive Sharpe ratio.

[4] Average allocations can mask the impact of the tactical allocation rules on portfolio compositions over time. Appendix 4 compares the portfolio compositions for each of the three TAA setups in the case of the equally-weighted strategy. The figure shows that, while the allocations are almost identical when averaged over time, the portfolio compositions often differ at any given point in time. In turn, this may result in diverging performance across investment strategies.

Table 3. Performance metrics for the 15 strategies when allocating across sectors

Risk and Return Metrics	Equally-Weighted			Capitalization-Weighted		
	No TAA	Vol.-Based	NAV-Based	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	-0.06%	0.29%	0.33%	-0.65%	-0.20%	0.00%
Ann. Avg. Geo. Price Return	-3.72%	-3.39%	-3.38%	-4.45%	-3.98%	-3.77%
Ann. Standard Deviation	22.40%	22.60%	22.50%	21.60%	21.80%	21.40%
Sharpe Ratio	-0.11	-0.09	-0.09	-0.14	-0.12	-0.11
Skewness	-0.33	-0.32	-0.34	-0.37	-0.36	-0.34
Kurtosis	10.1	10	10.5	8.9	9	8.8
Beta with Stocks	0.88	0.88	0.87	0.85	0.86	0.85
Maximum Drawdown	-80.40%	-80.30%	-80.00%	-76.40%	-77.00%	-76.50%
Value-at-Risk 95%	-41.30%	-41.10%	-40.90%	-39.10%	-38.90%	-38.80%
Value-at-Risk 99%	-57.80%	-57.70%	-57.70%	-52.20%	-53.10%	-52.60%

Risk and Return Metrics	Maximum Sharpe Ratio			Minimum Variance		
	No TAA	Vol.-Based	NAV-Based	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	4.92%	4.15%	3.73%	1.98%	1.87%	2.02%
Ann. Avg. Geo. Price Return	1.52%	0.68%	0.27%	-1.57%	-1.70%	-1.54%
Ann. Standard Deviation	24.00%	23.50%	23.40%	19.30%	19.60%	19.60%
Sharpe Ratio	0.11	0.08	0.06	-0.02	-0.02	-0.02
Skewness	-0.29	-0.31	-0.34	-0.53	-0.51	-0.53
Kurtosis	9.9	9.8	10.3	10.6	10.4	10.6
Beta with Stocks	0.81	0.82	0.82	0.7	0.73	0.73
Maximum Drawdown	-72.20%	-73.70%	-74.20%	-69.10%	-70.90%	-70.40%
Value-at-Risk 95%	-33.50%	-34.30%	-35.00%	-36.10%	-36.80%	-36.30%
Value-at-Risk 99%	-49.50%	-51.20%	-51.10%	-42.90%	-45.10%	-44.60%

Risk and Return Metrics	Risk Parity		
	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	-0.04%	0.34%	0.36%
Ann. Avg. Geo. Price Return	-3.69%	-3.33%	-3.33%
Ann. Standard Deviation	21.80%	22.00%	22.00%
Sharpe Ratio	-0.11	-0.09	-0.09
Skewness	-0.39	-0.37	-0.39
Kurtosis	10.2	10.1	10.6
Beta with Stocks	0.85	0.86	0.86
Maximum Drawdown	-79.90%	-79.90%	-79.60%
Value-at-Risk 95%	-41.50%	-41.20%	-41.10%
Value-at-Risk 99%	-56.80%	-56.80%	-56.80%

Sources: EPRA, Refinitiv Eikon, and authors' calculations.

The shape of the return distributions is comparable across strategies, with negative asymmetry (skewness ranging from -0.53 to -0.29) and fat tails (kurtosis ranging from 8.9 to 10.6). When considering downside risk, the equally-weighted strategy is the riskiest, with a maximum drawdown of 80.4% and a 99% VaR of 57.8%. Again, the minimum variance approach is better at controlling for risk, as it yields the lowest maximum drawdown (69.1%) and 99% VaR (42.9%).

Introducing tactical rebalancing leads to a total return improvement ranging from 35 to 65 bps for the equally-weighted, capitalization-weighted, and risk parity approaches. The NAV-based rule results in slightly higher total returns than the volatility-based rule. As the strategies' variance is only marginally higher when tactical allocation is considered, TAA results in higher Sharpe ratios. Implementing TAA has no meaningful impact on the shape of the distributions, nor on downside risk metrics.

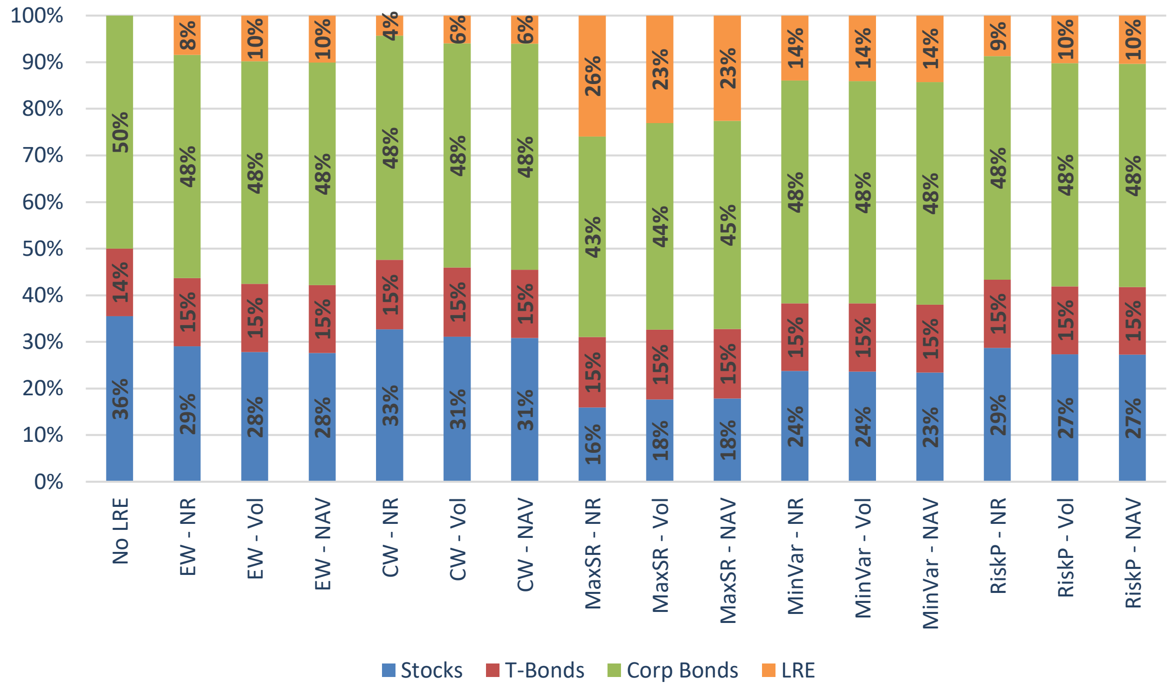
For the maximum Sharpe ratio approach, incorporating the tactical rebalancing rules results in total returns that are 77 and 119 bps lower for volatility-based and NAV-based TAA, respectively. Despite a reduction in return volatility (by 48 and 61 bps, respectively), these strategies present Sharpe ratios that are lower than without TAA. The worsening of the performance is due to the significant allocation of the TAA pockets to the diversified sector (for the volatility-based TAA) and to offices (for the NAV-based TAA). This reduces the industrial and residential allocations, which was the distinctive feature of the maximum Sharpe ratio portfolios. Finally, for the minimum variance strategy, TAA has no material impact on returns, Sharpe ratios, and downside risk metrics.

Overall, our results indicate that TAA is beneficial for allocation schemes that have relatively stable and well-balanced allocations. For those strategies, the flexibility provided by TAA makes it possible to seize opportunities that arise in high volatility or low price to NAV regimes. For the strategies that are inherently more dynamic, incorporating TAA is inconsequential at best and detrimental at worst. Those conclusions are robust when considering alternative assumptions regarding the TAA parameters (i.e., TAA duration, profit-taking level, and stop-loss level).

c. Mixed-Asset Portfolio Analysis

Figure 5 shows average allocations for portfolios consisting of stocks, government and corporate bonds, as well as LRE. The figure displays portfolio compositions for each strategy and for a portfolio that does not include LRE. Corporate bonds have the largest weight (almost 50%) for all strategies, while government bonds have a stable allocation at 15%. The allocation to stocks ranges from 16 to 36% and depends on whether LRE is included or not in the portfolio (i.e., a larger allocation to LRE coincides with a lower allocation to stocks, and inversely). The allocation to LRE ranges from 4% (capitalization-weighted strategy) to 26% (maximum Sharpe ratio strategy). This range is consistent with the evidence in the literature (Lee and Stevenson, 2005; MacKinnon and Al Zaman, 2009; Lizieri et al., 2022). Tactical rebalancing tends to increase the allocation to LRE.

Figure 5. Average mixed-asset portfolio allocations



Sources: EPRA and authors' calculations.

Notes: EW = Equally-Weighted, CW = Capitalization-Weighted, MaxSR = Maximum Sharpe Ratio, MinVar = Minimum Variance, and RiskP = Risk Parity. The TAAs are denoted by NR = No Rebalancing (i.e., no TAA), Vol = Volatility-Based, and NAV = NAV-Based. LRE refers to a portfolio diversified across sectors.

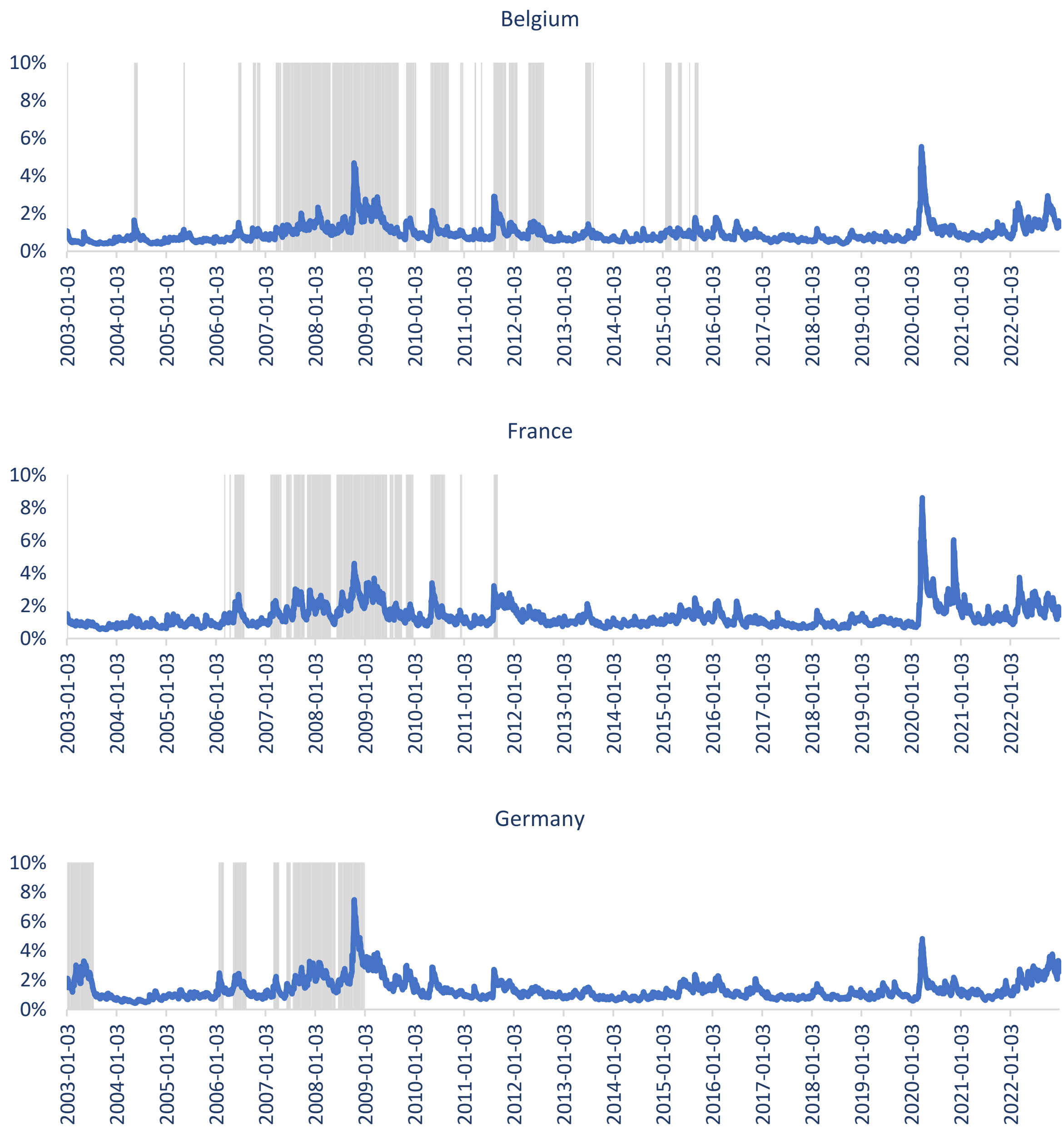
5.2. Country Analysis

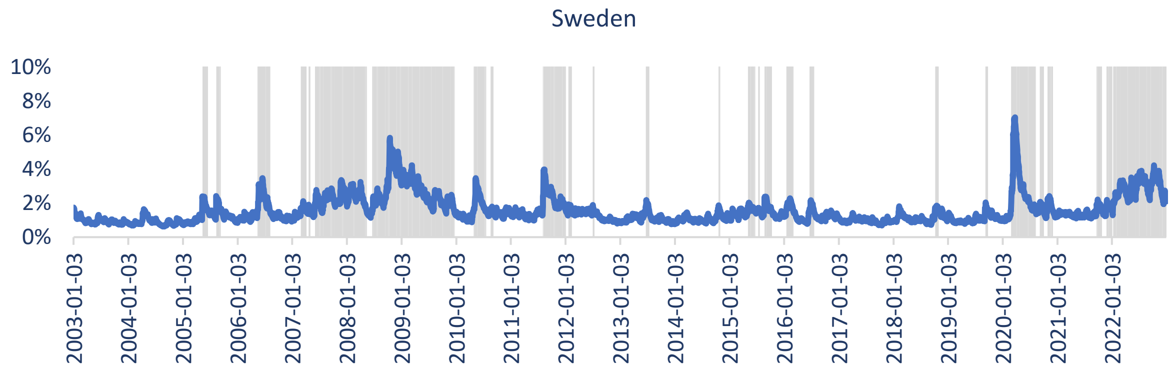
a. Time-Varying Volatility of Listed Real Estate Returns

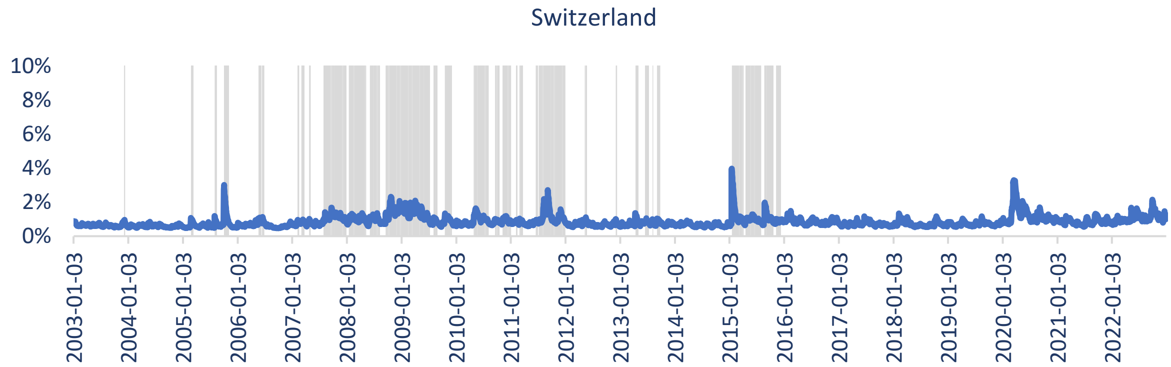
Considering countries, the examination of the ACFs and PACFs reveals the following ARMA-GARCH specifications: AR(1)-GARCH(1,1) for France, Germany, Sweden and the U.K. and AR(0)-GARCH(1,1) for Belgium and Switzerland. The GARCH model coefficients for countries are similar to those for sectors, with the effect of volatility persistence on current volatility dominating that of the previous period volatility shock (Appendix 5).

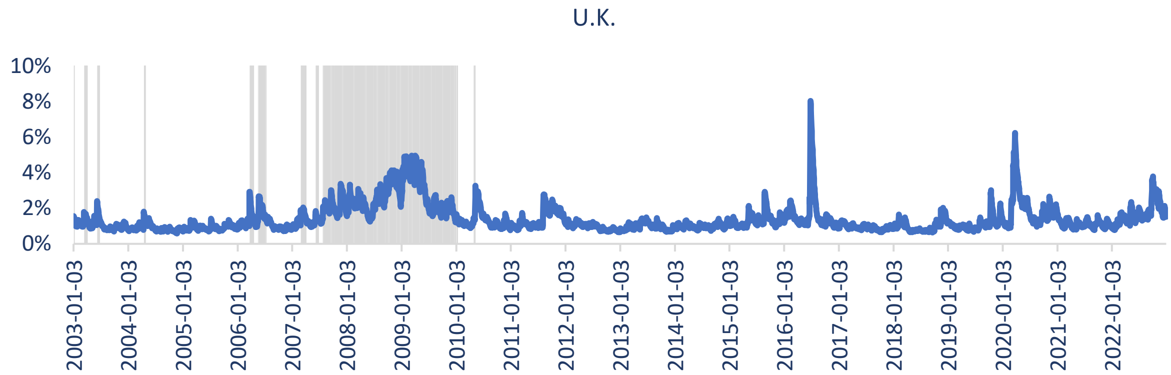
Figure 6 depicts the conditional volatility and the volatility regimes for the six countries. During the GFC, Germany and Sweden show the highest volatility (7.22% and 5.84%, respectively), while Switzerland (2.31%) is the least affected country. During the COVID-19 crisis, the most extreme daily volatility is observed for France (8.61%), while Switzerland has the lowest volatility (3.29%). The high volatility for France can be attributed to the high share of the office and retail sectors, which were badly hit by the pandemic (Hoesli and Malle, 2022). As is the case for the sector analysis, the GFC high-volatility regime lasts longer than the one of the COVID-19 pandemic. However, all countries except Germany experience higher volatility spikes during the COVID-19 pandemic than during the GFC. The contrasting result for Germany is due to the country's high market share of residential LRE, which was affected by the GFC but less so by the pandemic. Finally, the U.K. exhibits volatility spikes during the Brexit referendum period.

Figure 6. Volatility and volatility regimes of LRE by country









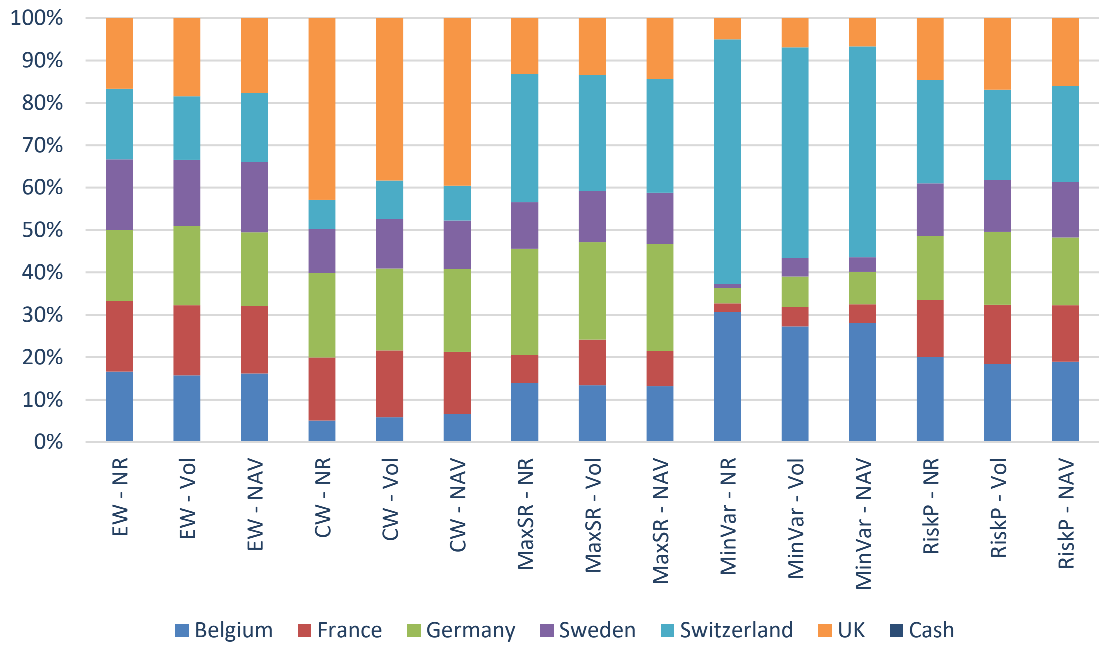
Sources: EPRA and authors' calculations.

Notes: The blue line is the estimated conditional volatility. Periods of high volatility are in grey, while periods of low volatility are in white.

b. Real Estate Portfolio Analysis

Figure 7 displays the average portfolio allocations of our strategies. As is the case when we allocate across sectors, the average allocation does not change significantly when tactical rebalancing is considered. Considering first the capitalization-weighted strategy, the U.K. has the largest allocation (roughly 40%), while Switzerland and Belgium have the smallest allocations (around 8% and 6%, respectively). However, these two countries have much larger allocations when considering the maximum Sharpe ratio, minimum variance and risk parity strategies. For the minimum variance strategy, for example, Switzerland represents as much as 52% of the portfolio, while Belgium accounts for 29%. This is attributable to the low volatility of these markets. Due to the U.K.'s weak performance, the allocation to that country is well below its market capitalization weight for the maximum Sharpe ratio, minimum variance and risk parity strategies. For the minimum variance strategy, the weight of Sweden is lower than its market weight, reflecting the high volatility of this market.

Figure 7. Portfolio compositions averaged over time for the 15 strategies



Sources: EPRA and authors' calculations.

Notes: EW = Equally-Weighted, CW = Capitalization-Weighted, MaxSR = Maximum Sharpe Ratio, MinVar = Minimum Variance, and RiskP = Risk Parity. The TAAs are denoted by NR = No Rebalancing (i.e., no TAA), Vol = Volatility-Based, and NAV = NAV-Based.

Table 4 exhibits the performance metrics for our 15 strategies. Considering first the case without TAA, the maximum Sharpe ratio and minimum variance strategies generate the highest total returns (10.25% and 10.20%, respectively). The strong performance of these strategies and of the risk parity allocation scheme (8.50%) is largely attributable to their substantial allocation to Switzerland and, to a lesser extent, Belgium. The capitalization-weighted strategy (5.79%) is the worst performing strategy. This can be explained by its high allocation to the U.K., which is the country with the worst performance. The minimum variance and risk parity strategies exhibit the lowest volatility (14.1% and 16.8%, respectively), while the capitalization-weighted strategy has the highest standard deviation (20.7%). The minimum variance strategy also exhibits the lowest downside risk metrics.

Table 4. Performance metrics for the 15 strategies when allocating across countries

Risk and Return Metrics	Equally-Weighted			Capitalization-Weighted		
	No TAA	Vol.-Based	NAV-Based	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	8.17%	7.69%	7.84%	5.79%	5.27%	6.04%
Ann. Avg. Geo. Price Return	3.95%	3.50%	3.61%	1.98%	1.43%	2.14%
Ann. Standard Deviation	18.50%	18.70%	18.60%	20.70%	20.40%	20.30%
Sharpe Ratio	0.3	0.27	0.28	0.16	0.13	0.17
Skewness	-0.35	-0.31	-0.35	-0.35	-0.35	-0.33
Kurtosis	10.5	10.4	10.6	9.4	9.7	9.5
Beta with Stocks	0.75	0.76	0.76	0.84	0.84	0.83
Maximum Drawdown	-65.20%	-66.20%	-65.20%	-75.90%	-74.80%	-74.40%
Value-at-Risk 95%	-30.10%	-31.30%	-30.60%	-37.40%	-37.30%	-36.30%
Value-at-Risk 99%	-41.30%	-42.90%	-41.50%	-50.30%	-49.60%	-49.00%

Risk and Return Metrics	Maximum Sharpe Ratio			Minimum Variance		
	No TAA	Vol.-Based	NAV-Based	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	10.25%	9.16%	10.06%	10.20%	9.35%	9.39%
Ann. Avg. Geo. Price Return	5.94%	4.86%	5.77%	5.95%	5.16%	5.15%
Ann. Standard Deviation	17.90%	17.60%	17.50%	14.10%	14.40%	14.40%
Sharpe Ratio	0.43	0.37	0.43	0.54	0.47	0.47
Skewness	-0.21	-0.22	-0.25	-0.24	-0.33	-0.29
Kurtosis	7.5	7.6	7.7	12	11.6	12.2
Beta with Stocks	0.53	0.57	0.57	0.41	0.48	0.47
Maximum Drawdown	-52.60%	-56.20%	-55.20%	-33.90%	-39.10%	-39.00%
Value-at-Risk 95%	-19.60%	-23.30%	-22.70%	-14.30%	-15.60%	-15.60%
Value-at-Risk 99%	-26.60%	-29.00%	-27.90%	-21.40%	-25.50%	-24.90%

Risk and Return Metrics	Risk Parity		
	No TAA	Vol.-Based	NAV-Based
Ann. Avg. Geo. Total Return	8.50%	8.10%	8.13%
Ann. Avg. Geo. Price Return	4.25%	3.90%	3.88%
Ann. Standard Deviation	16.80%	17.20%	17.10%
Sharpe Ratio	0.35	0.32	0.32
Skewness	-0.4	-0.35	-0.39
Kurtosis	11	10.7	10.9
Beta with Stocks	0.66	0.69	0.69
Maximum Drawdown	-58.60%	-60.40%	-59.80%
Value-at-Risk 95%	-25.90%	-27.20%	-26.80%
Value-at-Risk 99%	-34.90%	-36.90%	-36.30%

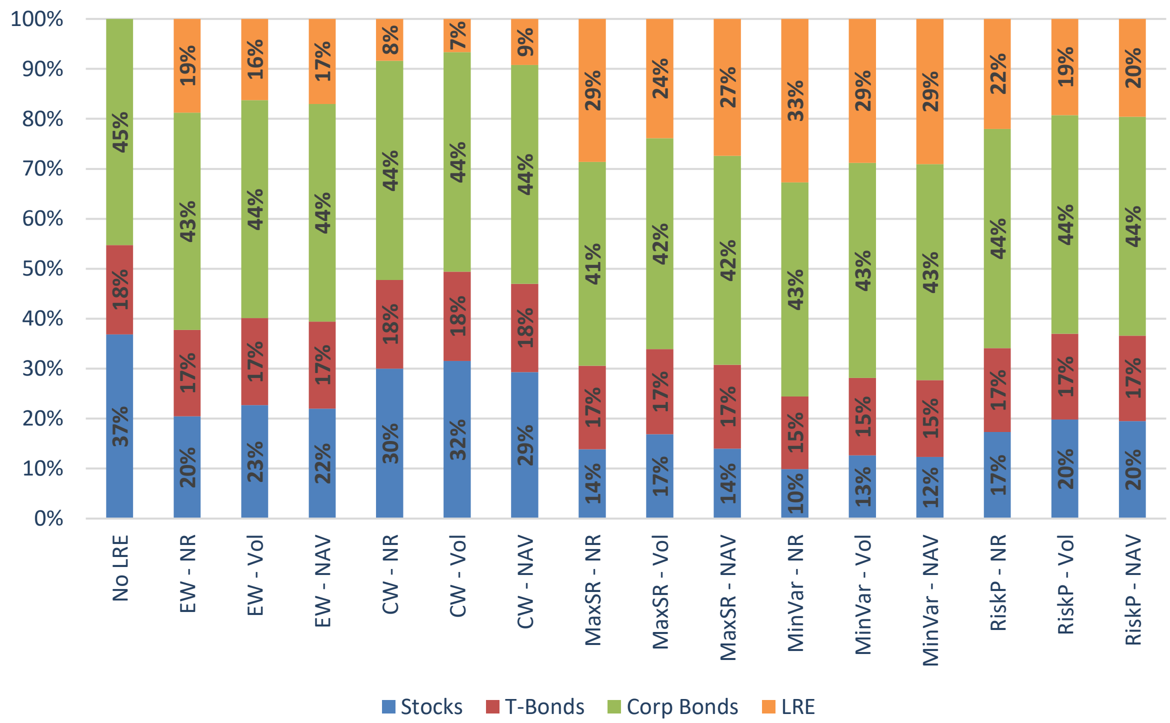
Sources: EPRA, Refinitiv Eikon, and authors' calculations.

Overall, TAA is detrimental when allocating across countries. The decline in total return ranges from -20 bps for the NAV-based TAA to -109 bps for the volatility-based TAA, both in the case of the maximum Sharpe ratio strategy. This is because TAA shifts the allocation away from Switzerland, and to a lesser extent Belgium, towards worse performing countries (France, Germany, and the U.K.). Only the NAV-based TAA applied to the capitalization-weighted strategy generates an incremental return of 25 bps. Given that TAA does not affect standard deviations, the same picture emerges for Sharpe ratios. Tactical rebalancing leads to higher downside risk for the two best performing strategies (i.e., the maximum Sharpe ratio and minimum variance strategies), while it has no effect on downside risk for the other strategies. As is the case for the sectoral allocations, those conclusions are robust when considering alternative assumptions for the TAA parameters.

c. Mixed-Asset Portfolio Analysis

Figure 8 shows average allocations for portfolios consisting of stocks, government and corporate bonds, as well as LRE. The figure displays portfolio compositions for each strategy and for a portfolio that does not include LRE. As in the sector analysis, corporate bonds have the largest weight (approximately 45%) for all strategies. The allocation to LRE is higher than in the sector analysis and ranges from 8% (capitalization-weighted strategy) to 33% (minimum variance strategy). As a result, the allocation to stocks tends to be lower. Tactical rebalancing leads to lower LRE allocations except for the capitalization-weighted NAV-based approach. The allocation to LRE is the highest for strategies that are more dynamic and allow for more concentrated positions (i.e., the maximum Sharpe ratio and minimum variance strategies), consistent with the sector analysis.

Figure 8. Average mixed-asset portfolio allocations



Sources: EPRA and authors' calculations.

Notes: EW = Equally-Weighted, CW = Capitalization-Weighted, MaxSR = Maximum Sharpe Ratio, MinVar = Minimum Variance, and RiskP = Risk Parity. The TAAs are denoted by NR = No Rebalancing (i.e., no TAA), Vol = Volatility-Based, and NAV = NAV-Based. LRE refers to a portfolio diversified across countries.

6. Conclusion

Our paper analyzes how the volatility of European LRE across sectors and countries has changed over the past two decades and how this information can be incorporated in a dynamic portfolio framework. The period under investigation is of interest as it includes three significant crises. We focus on the five main sectors of the LRE market, as well as on the six most important countries in terms of market capitalization.

The paper contributes to a better understanding of LRE volatility dynamics and the resulting implications for portfolio construction. First, our results provide evidence regarding the time-varying nature of European LRE volatility across sectors and countries, over several bear markets. Our second contribution is to assess whether the volatility of the public real estate market, as well as deviations from NAV, can be exploited to improve the performance of LRE portfolios. Finally, the effect of tactical rebalancing on the composition of a mixed-asset portfolio is considered.

In the first part of the analysis, we investigate how the volatility of European LRE has changed over time across sectors/countries. Our results show that volatility shocks are synchronous across sectors and countries, albeit with differences in magnitude. Overall, the GFC high-volatility regime lasts longer than that of the COVID-19 pandemic. The residential and industrial sectors show the highest volatility during the GFC, while offices and retail properties are less affected. During the COVID-19 crisis, the volatility of retail is the highest, while that of residential is the lowest. Finally, the recent surge in inflation has led to increased levels of volatility for all LRE sectors, although to a lesser extent than during the two previous crises. All countries but Germany experience higher volatility during the COVID-19 pandemic than during the GFC.

The second part focuses on the impacts of rule-based tactical rebalancing on the performance and composition of an LRE portfolio. We consider five strategic allocation approaches in conjunction with two tactical allocation methods. When allocating across sectors, TAA is beneficial for strategic asset allocation schemes that have stable and well-balanced allocations. For those schemes, the flexibility provided by TAA makes it possible to seize opportunities that arise in high volatility or low price to NAV regimes. For the more dynamic strategies, incorporating TAA is inconsequential at best and detrimental at worst. However, when allocating across countries, tactical rebalancing has a detrimental effect on LRE portfolio performance, as a result of the shift in allocations away from a well-performing country (Switzerland) to worse-performing countries. Those conclusions are robust to changes in TAA parameters.

The third part of the analysis tests whether tactical allocation affects the allocation to LRE in a mixed-asset portfolio also containing stocks and bonds. Our results indicate that the allocation to LRE ranges from 4% to 26% when sectors are considered, while it is slightly higher for countries. Overall, the LRE allocation is the highest for strategies that are more dynamic and allow for more concentrated positions in sectors/countries.

Most studies that have investigated the benefits of investing in LRE have done so by considering a buy-and-hold approach. This paper aims at expanding the literature by assessing the incremental performance that can be achieved by taking advantage of the daily liquidity and transparency of the LRE market. Our results demonstrate the usefulness for investors of considering publicly available information (i.e., price volatilities and premia/discounts to NAV) when allocating funds to LRE. This is especially the case for investors relying on stable and well-balanced portfolio allocation strategies, like most institutional investors. While our results suggest that TAA is more useful when allocating across sectors than across countries, it would be interesting to undertake the country (sector) analysis after controlling for the different sector (country) composition across countries (sectors). A worthwhile avenue for further research would be to use company-level LRE data to circumvent this limitation.

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Appendix

APPENDIX 1. SUMMARY STATISTICS OF TOTAL RETURNS FOR LRE SECTORS, STOCKS AND BONDS, 2013-2022

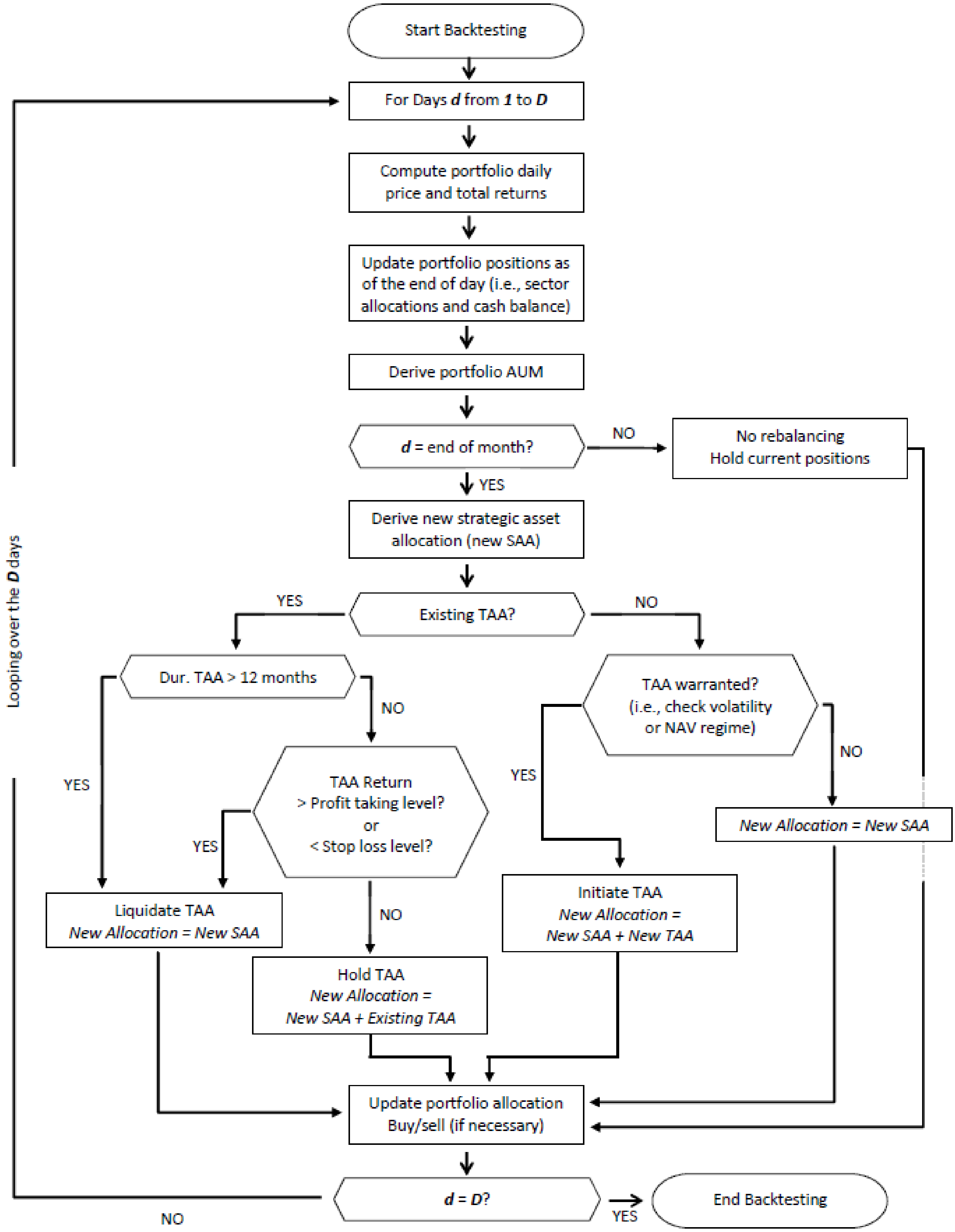
	Diversified	Industrial	Office	Residential	Retail	Stocks	Govt. Bonds	Corp. Bonds
Avg. Return (ann.)	6.30%	15.87%	7.10%	8.65%	-1.46%	8.78%	0.86%	0.68%
Geo. Avg. Ret. (ann.)	4.57%	14.47%	5.32%	6.82%	-5.92%	7.66%	0.76%	0.64%
Max. Return (daily)	8.38%	12.83%	11.74%	9.24%	22.57%	8.42%	1.88%	1.06%
Min. Return (daily)	-11.65%	-13.29%	-12.45%	-8.06%	-18.26%	-11.47%	-1.69%	-2.15%
St. Deviation (ann.)	19.07%	21.61%	19.55%	20.21%	30.60%	16.67%	4.62%	2.87%
Sharpe Ratio	0.20	0.63	0.23	0.30	-0.22	0.41	0.00	-0.04
Skewness	-0.82	-0.50	-0.28	-0.13	0.82	-0.84	-0.16	-1.20
Kurtosis	14.92	16.03	19.57	7.68	24.42	13.97	7.73	18.29
Value-at-Risk (95%)	-22.10%	-14.48%	-23.10%	-35.70%	-52.62%	-12.44%	-13.11%	-11.75%
Max. Drawdown	-43.98%	-76.17%	-48.07%	-60.30%	-81.04%	-35.34%	-21.90%	-17.72%
Nb. of Observations	2,567	2,567	2,567	2,567	2,567	2,567	2,567	2,567
Nb. of Years	10	10	10	10	10	10	10	10

Correlations	Diversified	Industrial	Office	Residential	Retail	Stocks	Govt. Bonds	Corp. Bonds
Diversified	1.00							
Industrial	0.81	1.00						
Office	0.92	0.79	1.00					
Residential	0.73	0.68	0.70	1.00				
Retail	0.77	0.54	0.74	0.49	1.00			
Stocks	0.75	0.65	0.70	0.60	0.62	1.00		
Govt. Bonds	0.18	0.22	0.20	0.28	0.10	0.06	1.00	
Corp. Bonds	0.32	0.32	0.34	0.33	0.20	0.19	0.78	1.00

Note: red stands for weak/negative correlation, yellow for moderate correlation (50th percentile), and green for strong correlation.

Sources: EPRA, Refinitiv Eikon, Bloomberg and authors' calculations.

APPENDIX 2. BACKTESTING FLOWCHART



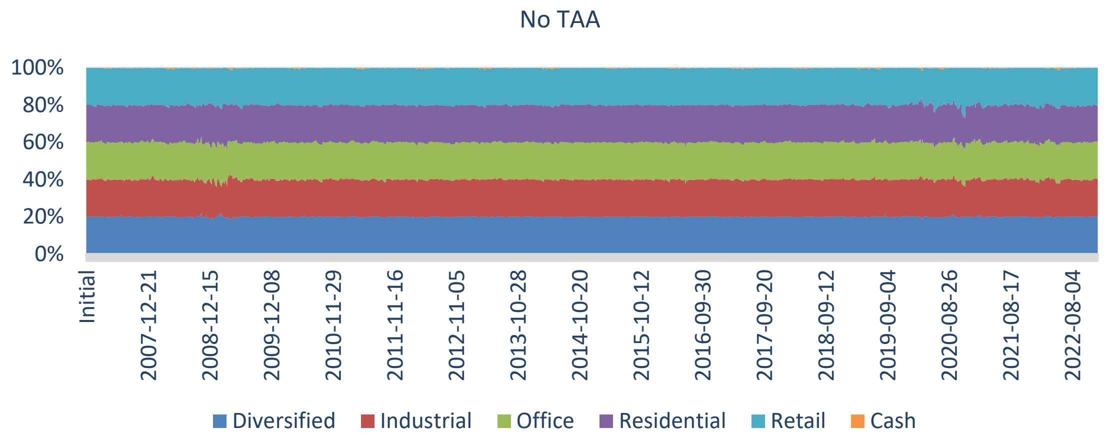
APPENDIX 3. ARMA-GARCH RESULTS FOR SECTORS

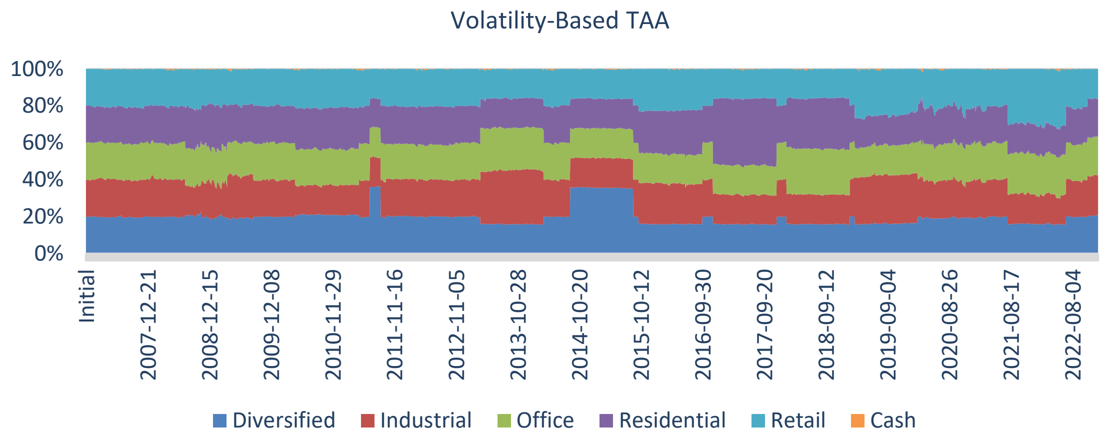
	Diversified AR(1)-GARCH(1,1)	Industrial AR(1)-GARCH(1,1)	Office AR(2)-GARCH(1,1)	Residential AR(1)-GARCH(1,1)	Retail AR(1)-GARCH(1,1)	Stocks AR(0)-GARCH(1,1)
			Mean Model			
Intercept	0.0481***	0.0695***	0.0532***	0.0636***	0.0153	0.0532***
AR(1)	0.0312*	0.0126	0.0388**	0.0497***	0.0421**	-
AR(2)	-	-	0.0042	-	-	-
			Volatility Model			
Intercept	0.0188***	0.0325***	0.0258***	0.0222***	0.0236***	0.0302***
α	0.1252***	0.1010***	0.1306***	0.0924***	0.1102***	0.1355***
β	0.8714***	0.8910***	0.8563***	0.9002***	0.8883***	0.8453***

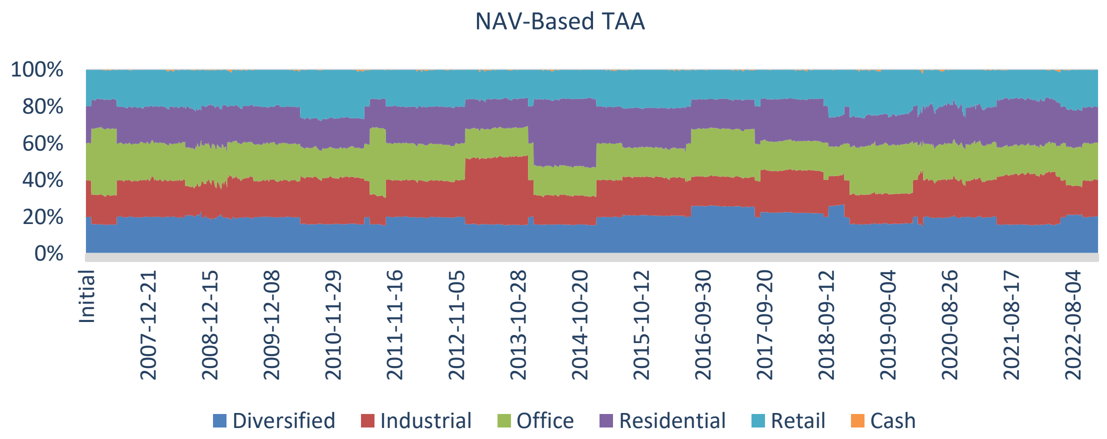
Notes: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Sources: EPRA, Refinitiv Eikon and authors' calculations.

APPENDIX 4. PORTFOLIO COMPOSITIONS FOR THE EQUALLY-WEIGHTED STRATEGY FOR SECTORS (THREE TAA SETUPS)







Sources: EPRA and authors' calculations.

APPENDIX 5. ARMA-GARCH RESULTS FOR COUNTRIES

	Belgium AR(0)-GARCH(1,1)	France AR(1)-GARCH(1,1)	Germany AR(1)-GARCH(1,1)	Sweden AR(1)-GARCH(1,1)	Switzerland AR(0)-GARCH(1,1)	U.K. AR(1)-GARCH(1,1)
			Mean Model			
Intercept	0.0375***	0.0606***	0.0578***	0.0825***	0.0372***	0.0558***
AR(1)	-	0.0264*	0.0468***	0.0382**	-	0.0224
AR(2)	-	-	-	-	-	-
			Volatility Model			
Intercept	0.0101***	0.0235***	0.0154***	0.0239***	0.0269**	0.0299***
α	0.0926***	0.1049***	0.0941***	0.0891***	0.1114***	0.1128***
β	0.9014***	0.8873***	0.9019***	0.9043***	0.8621***	0.8797***

Notes: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Sources: EPRA, Refinitiv Eikon and authors' calculations.