Securitized and Direct Real Estate in a Portfolio under Different Market Conditions[*]

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Abstract

We investigate whether and to what extent adding securitized real estate (SRE) to U.S. portfolios of stocks, bonds, and direct real estate affects portfolio performance and asset allocations. Our focus is on whether the results change under different market conditions. Using GARCH and Markov regime-switching models, we first analyze how the volatility of SRE across sectors has changed during the past 25 years. We aim to detect volatility episodes, particularly those related to specific events, and to examine whether the responses to crises vary across sectors. This highlights the importance of sector-level SRE exposure and provides the background for our portfolio analyses. We then utilize GDP and VIX data to estimate regimes with a Markov regime-switching model and use these to construct mixed-asset portfolios, both without and with SRE. We find that sectoral responses to the Global Financial Crisis (GFC) and the COVID-19 pandemic differ. Also, the high-volatility regime associated with the GFC lasts longer than that of the pandemic. We show that including SRE in a mixed-asset portfolio, particularly by considering the various sectors of the SRE market, improves risk-adjusted performance and that the allocation to SRE ranges from 3% to 28%. We also show that regime-switching strategies outperform static strategies on a risk-adjusted basis, though managing concentration risk is important. The study's results provide investors with a breakdown of portfolio assets under different market conditions. Furthermore, they should guide investors about how to allocate funds across sectors to form an SRE allocation.

Keywords: Securitized Real Estate; Direct Real Estate; Volatility; Crises; GARCH; Regime-Switching; Asset Allocation
JEL Codes: G11; R33; C22

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1. Introduction

Although securitized real estate (SRE) and direct real estate (DRE) have common economic drivers, the response of their returns to crises often differs in time and magnitude. These divergences arise from differences in liquidity, market transparency, ease of entry, and the efficiency of information transmission (Pagliari *et al.*, 2005; Ling and Naranjo, 2015). Whereas the public real estate market reacts quickly and sharply to a shock, the impacts are more muted and lagged for the private real estate market (Hoesli and Oikarinen, 2021). In this context, securitized and direct real estate are often viewed as complementary rather than substitutable investment vehicles. Investors either prioritize public markets for their greater liquidity and transparency or select direct real estate assets due to their lower correlation with stocks and bonds and greater diversification benefits (Hoesli and Oikarinen, 2012; Delfim and Hoesli, 2019). This paper considers both types of exposure to the asset class and investigates whether the SRE allocation in a mixed-asset portfolio varies with market conditions.

Much research has highlighted the diversification benefits of including direct real estate in mixed-asset portfolios (Pagliari, 2017; Delfim and Hoesli, 2019). In contrast, securitized real estate contributes less to portfolio diversification due to its higher correlation with stocks and bonds (Abuzayed *et al.*, 2020; Lizieri *et al.*, 2022). However, its diversification potential increases over longer investment horizons, as underlying fundamentals play a dominant role in return behavior in the long run (Hoesli and Oikarinen, 2012 and 2021). While public real estate is generally more vulnerable to market distress than its private counterpart (Caporin *et al.*, 2021; Hoesli *et al.*, 2025), sector-specific responses to crises can vary significantly between the two types of exposure (Ling *et al.*, 2020; Milcheva, 2022). Securitized real estate can thus play a role in mixed-asset portfolios, also when considered alongside direct real estate (NAREIT, 2011).

To gauge the diversification potential of real estate investments more fully, this paper seeks to assess the role of securitized real estate in a portfolio of U.S. assets. Specifically, we investigate whether adding SRE to portfolios of domestic stocks, bonds, and direct real estate affects performance and allocations, and whether the results differ across periods of market turmoil and periods of stability. We also aim to explore the composition of the SRE bucket by considering traditional and alternative sectors, as well as mortgage real estate investment trusts (REITs). Broadening the analysis beyond traditional property types widens the opportunities available to investors, particularly in light of recent research emphasizing the growing potential of alternative sectors in improving the risk-return profile of institutional portfolios (Fitzgerald *et al.*, 2025). These sectors are increasingly shaped by structural trends such as population ageing, urbanization, and digitalization

(Newell and Marzuki, 2023). Moreover, studies have examined the potential benefits of including mortgage REITs in institutional portfolios, highlighting their distinct return drivers (Hansz *et al.,* 2017).

The period under investigation, 2000-2024, is of interest as it includes four significant crises: the dotcom crash, the Global Financial Crisis (GFC), the COVID-19 pandemic, and the recent surge in interest rates and high inflation. The dotcom crash was driven by speculative overvaluation and the bursting of a technology bubble, while the GFC, as a credit crisis, mainly disrupted capital availability and caused significant stress. In contrast, the COVID-19 pandemic disrupted the operations of many commercial tenants and altered the outlook for real estate demand. Finally, the shock associated with inflation and interest rate increases, as a result of growing geopolitical instability, led to a significant downward revision of real estate asset values and dampened investors' outlook. The distinct nature of these crises makes the selected period a well-suited sample for capturing volatility regimes and evaluating portfolio strategies under various market conditions.

To investigate the volatility dynamics of SRE over time and across sectors, we first apply a GARCH model to estimate volatilities and then identify volatility-based regimes with a Markov regime-switching model. We aim to detect volatility episodes related to specific events and to examine whether the responses to crises vary across sectors, providing the background for our portfolio analyses. We then use a Markov regime-switching model to estimate GDP- and VIX-based regimes and construct mixed-asset portfolios based on these, both without and with SRE. Given that real estate sectors are likely to react differently to shocks, we are particularly interested in the composition of the SRE bucket and its variation depending on market conditions. This sector-specific behavior may offer investors opportunities to enhance portfolio diversification and risk-adjusted returns (Moss *et al.*, 2017; Cai and Xu, 2022; Chaudhry *et al*., 2022). We also consider an aggregate SRE index to assess the added value of sector-level allocations rather than market-based allocations.

Our regime-switching framework applies a maximum Sharpe ratio approach during low-risk periods, with the aim of maximizing risk-adjusted returns in favorable economic conditions. In contrast, during high-risk environments, the strategy switches to a minimum variance approach to prioritize risk reduction. To maintain practical relevance, we implement this strategy using a 36-month rolling window. For direct real estate investments, we consider a fixed target weight of 10%, although alternative targets are considered for robustness checks. To account for illiquidity and high transaction costs of the asset class, we impose a longer holding period and rebalance the weight of DRE back to the target once every three years only, while rebalancing stocks, bonds, and SRE at a quarterly frequency (at a monthly frequency for the VIX-based strategy). To avoid look-ahead bias, all portfolio decisions are based solely on information available at the time of rebalancing.

Our results for the first part of the analysis highlight the importance of sector-level SRE exposure, showing that real estate sectors react differently to crises. Self-storage, apartment, and healthcare sectors prove most resilient, while office, retail, and hotel properties were more strongly affected. We also find that the high-volatility regime of the GFC lasts longer than that of the pandemic, reflecting the more systemic nature of the crisis. During the post-2022 period, volatility, although less pronounced than during previous crises, increased across most sectors, with mortgage and office REITs showing the strongest reactions, while healthcare, self-storage, and apartment sectors remained comparatively stable.

In the context of mixed-asset portfolio performance, our results highlight three key findings. First, the inclusion of SRE improves risk-adjusted performance across all strategies. For example, for the maximum Sharpe ratio strategy, adding an aggregate SRE index increases the Sharpe ratio from 0.59 to 0.67 compared to a baseline portfolio without SRE. Similarly, for the GDP-based regime-switching strategy, the Sharpe ratio rises from 0.62 to 0.71 when SRE is included. Second, sector-based strategies outperform those relying on an aggregate SRE index, though managing concentration risk is important. The effect is most pronounced for the minimum variance strategy, where the Sharpe ratio increases from 0.50 for the aggregate SRE index to 0.60 for the sector-based approach. Third, the regime-switching framework generally outperforms the static strategies on a risk-adjusted basis, with performance depending on the effectiveness of constraints in limiting concentration risk. Taken together, the maximum Sharpe ratio and GDP-based regime-switching approaches perform best when sectoral SRE weights are capped at 10%, with Sharpe ratios of 0.68 and 0.72, respectively. For the minimum variance strategy, the highest Sharpe ratio (0.60) is achieved both with uncapped sector weights and with a 10% sector cap. In the VIX-based setup, the highest Sharpe ratio (0.71) is obtained under a 5% sector cap. Relative to the GDP-based strategy, the VIX-based strategy shows slightly lower performance. This likely reflects the different nature of VIX-based regimes, which are less stable and more sensitive to short-term market dynamics.

Concerning portfolio allocations, we find that the regime-switching strategies produce more diversified portfolios across stocks, bonds, and SRE, with asset weights that are in-between those of the two static approaches. The allocation to sector-level SRE ranges from 3% (minimum variance strategy) to 16% (maximum Sharpe ratio strategy) for portfolios where we limit the weight of each sector to 10%, while it is from 3% to 28% when no limits are imposed. Under the regime-switching strategies, average SRE allocations are moderate and slightly higher in the VIX-based setup than in the GDP-based setup. The allocations are 10% (GDP) versus 12% (VIX) with the 10% cap and 17% (GDP) versus 20% (VIX) when sector weights are unrestricted.

From a practical point of view, the findings of this paper should be relevant for institutional investors, portfolio managers, and individual investors seeking to benefit from SRE allocations in mixed-asset portfolios. For institutional investors, who typically follow conservative and long-term strategies, the results highlight how SRE can complement direct real estate holdings within a strategic asset allocation framework. For institutional investors with more active mandates, as well as other investment professionals, the regime-switching approach offers a framework for dynamically adjusting allocations in line with changing market conditions. In this context, GDP-based regimes serve as a stable macroeconomic benchmark suited for longer-term strategies, while VIX-based regimes complement this perspective by capturing higher-frequency shifts in investor risk perception, making them applicable to shorter-horizon market participants. Finally, for individual investors, the study provides guidance for sectoral allocation decisions during crises, with healthcare, self-storage, and apartments proving most defensive, while offices, retail, and hotels are more vulnerable. Overall, the liquidity of SRE and its accessibility through exchange-traded funds (ETFs) make it a practical tool for gaining real estate exposure without large capital commitments, though balancing opportunities with concentration risk is important.

The remainder of the paper is structured as follows. In section 2, we present a literature review before discussing the data in section 3. Section 4 describes our methodology, while the results are analyzed in section 5. Section 6 concludes.

2. Literature Review

Much research has documented the diversification benefits of adding direct real estate to mixed-asset portfolios (Pagliari, 2017; Delfim and Hoesli, 2019). For a given return, portfolio risk has been shown to decrease by about 15% when real estate is included in a portfolio. The effects of including SRE are more muted due to their higher correlation with financial assets, especially during crises (Abuzayed *et al.*, 2020; Lizieri *et al.*, 2022). However, the benefits of holding SRE increase with the time horizon (MacKinnon and Al Zaman, 2009). This is consistent with the evidence that, over mid- to long-term horizons, securitized real estate becomes more akin to direct real estate, as the drivers of both asset classes are the same (Hoesli and Oikarinen, 2012 and 2021).

In the literature, evidence suggests that the optimal allocation to SRE and DRE in a portfolio is 5-25%. According to Hoesli *et al.* (2004), the allocation to direct real estate ranges from 5 to 15% for unhedged returns and from 15 to 25% for hedged returns. Concerning securitized real estate, Lee and Stevenson (2005) find that the allocation for U.S. investors should be between 10 and 18%. Some studies show that it is useful to combine public and private real estate in a portfolio, as they are not fully substitutable and may play complementary roles (Bessell *et al.*, 2025). For instance, NAREIT

(2011) finds that an optimal combination (a split of two-thirds/one-third) of real estate funds and public real estate produces higher risk-adjusted returns compared to investing in private vehicles alone. Mueller and Mueller (2024) perform mixed-asset portfolio analyses over a 45-year period covering six economic cycles and four real estate cycles. They find that both direct real estate and REITs enhance historical portfolio performance, but do not provide any evidence concerning REIT and DRE sectors.

The optimal allocation to real estate depends on the investment horizon, generally increasing as the horizon lengthens. MacKinnon and Al Zaman (2009) show that the allocation to direct real estate in mixed-asset portfolios rises over medium and long horizons, primarily due to its declining correlations with stocks and bonds. Fugazza *et al.* (2007) find that European real estate represents an attractive long-term asset class within mixed-asset portfolios, with increased returns over extended investment horizons. In contrast, Hoevenaars *et al*. (2008) show that the return dynamics of U.S. REITs are largely captured by those of stocks and bonds, with REIT returns exhibiting only mild mean reversion over the long run, making them a less attractive component for long-horizon portfolios.

The share of real estate in institutional portfolios of U.S. investors has increased over the past decades. For instance, U.S. pension funds have doubled their real estate allocations from 5% in 1993 to 10% in 2023 (Carlo *et al*., 2021; Equable Institute, 2023). Despite this growth, a persistent gap remains between the real estate allocations suggested by academic research and those observed in practice, with actual allocations typically representing only about half of the suggested levels. This can be attributed to several factors. First, the illiquidity of real estate, combined with high transaction and management costs, as well as asset heterogeneity and idiosyncratic risk, likely discourage investors from taking higher exposures (Hoesli *et al*., 2003; Pagliari, 2017). Second, investor-specific risk-return preferences may lead to a bias toward portfolios positioned higher on the efficient frontier, favoring stocks over real estate. Third, institutional investors often adopt an asset-liability management framework rather than an asset-only perspective, which typically implies lower optimal allocations to real estate (Johner and Hoesli, 2025).

During periods of market distress, extensive research shows that such periods have severe effects on the performance of securitized real estate (Hoesli and Reka, 2013; Milcheva and Zhu, 2018; Caporin *et al.*, 2021; Hoesli *et al.*, 2025), while the impacts are more muted for direct real estate (Hoesli and Malle, 2022 and 2023). Studies also show that real estate sectors react differently to crises. During the GFC, industrial and self-storage properties were least affected due to their defensive nature (Chaudhry *et al*., 2022). However, the volatility of the industrial sector was higher compared to that of the self-storage sector (S&P Dow Jones Indices, 2020). During the COVID-19 pandemic, the retail and residential sectors experienced the worst performance, while technology and healthcare properties had a positive response (Ling *et al.*, 2020; Milcheva, 2022). The strong performance of technology properties likely results from the rapid development of e-commerce and the extensive implementation of online communication tools during the pandemic (NAREIT, 2021; Cai and Xu, 2022).

In recent research, Umar and Teplova (2025) examine return and volatility linkages between U.S. sectoral REITs and yield curve components from the early 2000s dotcom crash to the COVID-19 pandemic and find that infrastructure, mortgage, and timber REITs consistently act as diversifiers during stable periods, while they serve as safe havens during market turbulence. Similarly, Bahlous-Boldi *et al.* (2025) analyze the effects of the Economic Policy Uncertainty index on U.S. REIT sectors from 1994 to 2024 and show that REIT sectors are highly interconnected. Retail properties emerge as key shock transmitters, while self-storage, manufactured homes, and industrial REITs demonstrate greater resilience. They also find that the volatility drivers shift across crises, with residential REITs dominating during the GFC and the office sector being the primary source of disruption during the recent pandemic.

There is a growing body of research investigating the rise of alternative real estate sectors (Arnold *et al.*, 2023; Newell and Marzuki, 2023), as well as adding mortgage REITs to institutional real estate portfolios (Hansz *et al.*, 2017). The real estate market is currently experiencing a notable shift to alternative sectors due to the reshaping impact of megatrends such as ageing population, urbanization, and digitalization (EPRA, 2024). In this context, Fitzgerald *et al.* (2025) find that holding data centers, self-storage, life sciences, and other non-traditional property types enhances the risk-return profile of institutional real estate portfolios. Concerning mortgage REITs, Hansz *et al.* (2017) show that the returns of equity and mortgage REITs have different driving factors, and hence that the two types of exposure are not substitutable. Adding mortgage REITs to a portfolio may provide investors with greater diversification benefits, compared to including equity REITs only.

A number of studies have explored the usefulness of regime-switching strategies in a portfolio context. For instance, Ang and Bekaert (2002) show that international diversification is more effective when changes in regimes are accounted for. Similarly, Guidolin and Timmermann (2007) find that optimal portfolio allocations vary substantially across regimes, both in-sample and out-of-sample. Finally, Bulla *et al.* (2011) apply a Markov regime-switching model to daily returns of major stock indices in the U.S., Japan, and Germany and demonstrate that the strategy is effective out-of-sample, even after accounting for transaction costs. The results show an average reduction in portfolio risk of 41% and annualized excess returns between 18.5 and 201.6 basis points, thus highlighting the potential of regime-based strategies in outperforming static approaches. More recently, Strauss and Williams (2025) find that a regime-switching strategy that exploits time-varying correlations across major asset classes, including REITs, improves risk-adjusted performance relative to a static strategy.

Likewise, Thomson (2025) applies a machine learning regime classifier to ETF portfolios and shows that a regime-based strategy improves out-of-sample performance relative to static benchmarks.

Some research has specifically examined securitized real estate within regime-switching frameworks. Demiralay and Kilincarslan (2024) employ a non-linear Markov regime-switching model to explore the relationship between REIT sectors and various uncertainty measures. Their findings reveal asymmetric and sector-specific linkages, with residential REITs showing the greatest resilience and healthcare REITs being adversely affected by all uncertainty factors, but only in low-volatility regimes. Similarly, Essa and Giouvris (2025) apply a Markov regime-switching model with VIX as a regime indicator and find that herding behavior across U.S. REIT sectors increases during crisis periods, with the strongest effects being during the COVID-19 pandemic.

3. Data

We use monthly index-level U.S. data for the period 2000-2024. We determine the length and scope of the time series based on the availability of data across the three key types of sectors (i.e., traditional, alternative, and mortgage) and/or by the importance of real estate sectors based on market capitalization. Additionally, we ensure that only sectors with at least three constituents are included. Thus, data were gathered for the five traditional SRE sectors (i.e., apartments, hotels, industrial, office, and retail), two alternative SRE sectors (i.e., healthcare and self-storage), and two types of mortgage REITs (i.e., commercial financing and home financing). Additionally, we include an aggregate SRE index in the analysis. An aggregate index reflects how investors typically gain exposure to SRE (i.e., through broad-based indices rather than sector-level allocations). This can be achieved through the purchase of ETFs that are designed to replicate the performance of broad-based SRE indices and provide a diversified, liquid, and cost-efficient means of accessing the SRE market. Furthermore, the aggregate index serves as a benchmark to assess the added value of considering sectoral allocations. Sector-level results are expected to differ from those of the aggregate index, as the latter tends to smooth sector-specific responses to market shocks through diversification effects. At the same time, allocating too heavily to certain sectors can increase concentration risk, especially during periods of sector-specific underperformance. To address this, we consider a 10% limit on each sector’s weight, ensuring that there is no excessive exposure to any single sector.

We source SRE data from the NAREIT website. Specifically, we use the FTSE NAREIT sector price and total return indices. For aggregate SRE portfolio analyses, we utilize the FTSE NAREIT All REITs total return index. We use the CoStar U.S. Investment Grade equally-weighted commercial repeat-sales (CCRSI) index comprising hotel, industrial, multifamily, office, and retail properties for direct real estate.[1] We select an equally-weighted index as we do not want to impose the dominance of any single transaction in the representation of DRE performance. Given that the CoStar data concern capital returns only, we employ quarterly NCREIF Property Index (NPI) income return data to generate total return estimates. Specifically, we use linear interpolation to convert the quarterly NPI income return data to a monthly frequency and then add the interpolated income returns to the CoStar capital returns to construct a total return series for direct real estate. To account for capital expenditures (CAPEX) in our DRE total return series, we apply a 1.5% annual CAPEX adjustment (Bokhari and Geltner, 2019). The CoStar CCRSI indices are transaction-based and constructed using the repeat sales approach, therefore, we do not desmooth direct real estate data. Stock price and total return indices, as well as government and corporate bond total return indices are collected from the Bloomberg database. Specifically, these are the S&P 500, Bloomberg U.S. Corporate Bond, and S&P U.S. Treasury Bond Current 10-Year indices. The U.S. 3-month T-Bill, used as a proxy for the risk-free rate, the nominal GDP data, and the VIX volatility index data are from the Federal Reserve Bank of St. Louis (FRED) website. All data are in U.S. dollars.

Figure 1 shows total return indices for SRE sectors and stocks.[2] Most sectors exhibit similar patterns over time, with the self-storage sector experiencing the largest growth following the GFC. This growth is likely driven by increased demand for storage spaces due to urbanization and greater population mobility, as well as the sector's expansion and value convergence as an emerging institutional asset class. In contrast, commercial financing REITs declined sharply during the GFC, likely reflecting the impact of tighter credit regulations. Notably, home financing REITs did not show a comparable decline during the same period. However, the number of home financing REITs fell significantly, from 25 in 2006 to just 10 in 2008, indicating a substantial contraction in the sector.[3] This reduction suggests the presence of survivorship bias, as many weaker REITs exited the index. As a result, the apparent resilience of home financing REITs during the GFC may be misleading.

[1] Appendix 1 presents price returns for the CoStar Investment Grade commercial real estate index. According to CoStar, the Investment Grade index captures larger-sized, reasonable-quality properties that are representative of assets most commonly acquired by institutional investors.
[2] Appendix 2 shows price return indices for SRE sectors and stocks.
[3] Appendix 3 shows the number of mortgage REITs included in the FTSE NAREIT Home Financing and Commercial Financing indices over time, from 2000 to 2024.

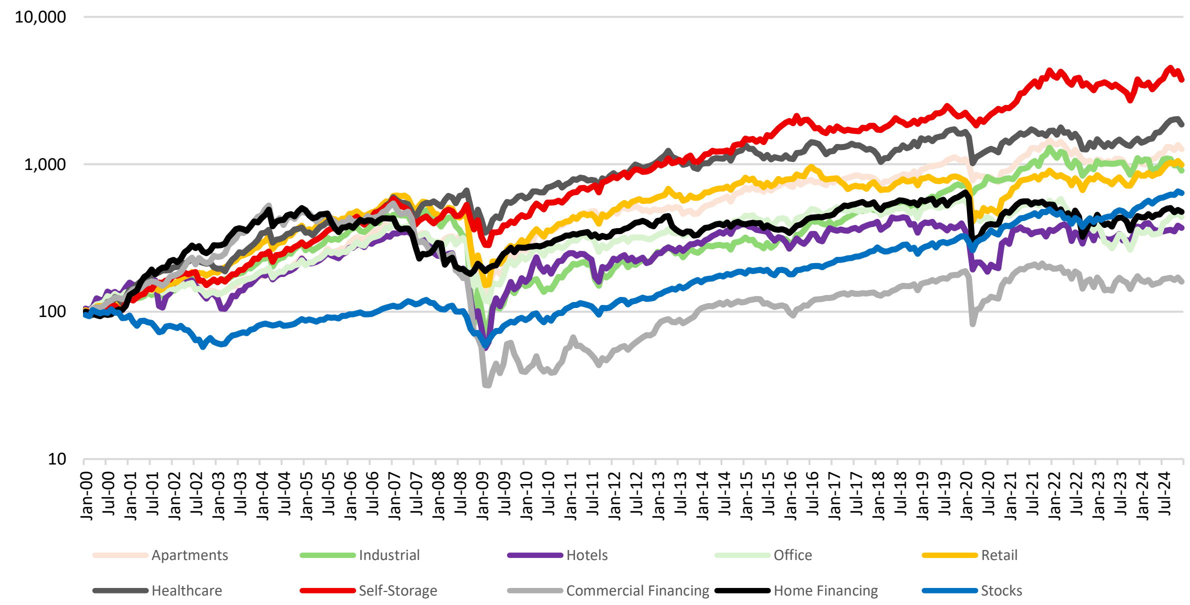

Figure 1. Total Return Indices for Securitized Real Estate Sectors and Stocks, 2000-2024.

Sources: NAREIT, Bloomberg, and authors' calculations.

Note: The vertical axis is presented on a logarithmic scale.

Table 1 presents summary statistics for stocks, government bonds, corporate bonds, DRE, and SRE aggregate. The sample consists of 300 monthly observations for 2000-2024. SRE delivers the highest annualized average return (11.21%), followed by stocks (8.62%) and DRE (7.98%), while the returns of corporate and government bonds, as expected, are lower (4.97% and 3.96%, respectively). In terms of risk, SRE exhibits the highest annualized standard deviation (19.89%) and the most extreme monthly returns, both positive (27.97%) and negative (-30.23%). In contrast, corporate bonds and DRE have the lowest risk among all assets (6.25% and 6.57%, respectively). Considering the shape of the return distribution, all assets exhibit negative skewness, except government bonds, due to the downward trend in interest rates over the period. The positive excess kurtosis indicates that all series have fatter tails than the normal distribution. The difference between the arithmetic and geometric average annualized returns is most pronounced for SRE (11.21% and 9.56%, respectively) and stocks (8.62% and 7.70%, respectively), reflecting the higher volatility of these assets. Correlation analysis reveals that stocks are strongly correlated with SRE (0.67), as expected, but exhibit a near-zero positive correlation with DRE (0.01). Interestingly, SRE and DRE themselves are weakly positively correlated (0.10). This highlight the potential diversification benefits of including DRE in mixed-asset portfolios. While SRE offers higher returns, its elevated volatility and strong correlation with the stock market make it more sensitive to shocks. In contrast, DRE delivers more stable, uncorrelated performance, which can be valuable during periods of distress.

Table 1. Summary Statistics of Total Returns for Stocks, Bonds, and Real Estate, 2000-2024.

	Stocks	Corp. Bonds	Govt. Bonds	DRE	SRE Agg.
Arithmetic Average (Ann.)	8.62%	4.97%	3.96%	7.98%	11.21%
Geometric Average (Ann.)	7.70%	4.88%	3.73%	8.04%	9.56%
Maximum Return (Monthly)	12.82%	6.80%	9.80%	7.07%	27.97%
Minimum Return (Monthly)	-16.80%	-7.77%	-7.08%	-6.91%	-30.23%
Standard Deviation (Ann.)	15.32%	6.25%	7.61%	6.57%	19.89%
Skewness	-0.49	-0.61	0.14	-0.66	-0.86
Kurtosis	3.79	6.46	4.05	4.64	8.45
# of Observations	300	300	300	300	300
Correlations	Stocks	Corp. Bonds	Govt. Bonds	DRE	SRE Agg.
Stocks	1.00				
Corp. Bonds	0.36	1.00			
Govt. Bonds	-0.16	0.63	1.00		
DRE	0.01	-0.01	0.00	1.00	
SRE Agg.	0.67	0.50	0.08	0.10	1.00

Sources: NAREIT, Bloomberg, and authors' calculations.

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

Table 2 presents summary statistics across nine SRE sectors. The sample consists of 300 monthly observations for 2000-2024. The self-storage sector achieves the highest average return (16.96%), followed by healthcare (14.45%), and industrial (13.95%). In contrast, commercial financing (7.35%) and home financing (9.65%) REITs exhibit the lowest returns, while offices (8.80%) also underperform relative to other property sectors. Hotels (33.13%), industrial (30.97%), and commercial financing (31.10%) properties have the highest risk. The industrial sector and home financing REITs also show high excess kurtosis (22.36 and 17.15, respectively), indicating the presence of extreme returns. Skewness is negative across most sectors, but particularly in home financing (-2.19) and commercial financing (-1.40) REITs. The difference between arithmetic and geometric average returns varies widely across SRE properties, with the largest discrepancies observed in the riskiest sectors, such as hotels (10.62% and 5.37%, respectively) and commercial financing (7.35% and 1.89%, respectively). Correlations across traditional sectors (i.e., apartments, offices, and retail) are high, exceeding 0.75, which may be attributable to common macroeconomic drivers. In contrast, home financing REITs show weaker correlations with other sectors (ranging from 0.33 to 0.64). Overall, there is heterogeneity in return and risk profiles across SRE sectors, underscoring the potential for sectoral diversification within real estate portfolio allocations.

Table 2. Summary Statistics of Total Returns for SRE Sectors, 2000-2024.

	Apartments	Industrial	Hotels	Office	Retail	Healthcare	Self-Storage	Commercial Financing	Home Financing
Arithmetic Average (Ann.)	12.47%	13.95%	10.62%	8.80%	12.61%	14.45%	16.96%	7.35%	9.65%
Geometric Average (Ann.)	10.69%	9.21%	5.37%	6.08%	9.61%	12.40%	15.59%	1.89%	6.43%
Maximum Return (Monthly)	23.14%	70.48%	67.52%	32.46%	43.52%	27.73%	21.93%	37.46%	18.51%
Minimum Return (Monthly)	-26.83%	-56.19%	-36.56%	-31.80%	-42.68%	-33.45%	-22.24%	-52.09%	-54.49%
Standard Deviation (Ann.)	21.10%	30.97%	33.13%	23.81%	25.29%	22.96%	21.81%	31.10%	24.28%
Skewness	-0.65	0.18	0.88	-0.22	-0.77	-0.68	-0.25	-1.40	-2.19
Kurtosis	5.99	22.36	13.56	6.94	13.50	6.85	4.02	11.23	17.15
# of Observations	300	300	300	300	300	300	300	300	300
Correlations	**Apartments**	**Industrial**	**Hotels**	**Office**	**Retail**	**Healthcare**	**Self-Storage**	**Commercial Financing**	**Home Financing**
Apartments	1.00								
Industrial	0.67	1.00							
Hotels	0.68	0.62	1.00						
Office	0.82	0.77	0.75	1.00					
Retail	0.80	0.75	0.79	0.87	1.00				
Healthcare	0.74	0.69	0.60	0.77	0.81	1.00			
Self-Storage	0.69	0.67	0.52	0.66	0.67	0.68	1.00		
Commercial Financing	0.67	0.55	0.67	0.71	0.73	0.64	0.45	1.00	
Home Financing	0.42	0.34	0.42	0.50	0.53	0.53	0.33	0.64	1.00

Sources: NAREIT, Bloomberg, and authors' calculations.

Notes: Yellow stands for moderate correlation (50th percentile) and green for strong correlation.

4. Methodology

4.1. Time-Varying Volatility of Securitized Real Estate Returns

We start by examining volatility spikes in the price returns of traditional, alternative, and mortgage SRE sectors. For each sector, we estimate an ARMA(p,q)-GARCH(1,1) model that captures both the conditional mean and the conditional volatility of the series. We select the orders for the AR(p) and MA(q) parts of the mean model by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. A GARCH(1,1) model is preferred for its parsimony. Both parts of the model are estimated simultaneously using a maximum likelihood method. We conduct additional diagnostic tests to confirm that the residuals satisfy model assumptions.

We then apply a Markov regime-switching model (Hamilton, 1989) to the estimated volatility series to identify high and low regimes. Markov models are used 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:

$$y_t = \mu_{s_t} + \varepsilon_{s_t} \tag{1}$$

with: $$\varepsilon_{s_t} \sim \text{i.i.d. } N(0, \sigma_s^2)$$

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, assumed to be independent and identically normally distributed within each regime, $N(0, \sigma_s^2)$, with mean zero and variance σ_s^2 that may differ across regimes. A transition probability matrix with two states (i.e., high and low volatility regimes) is used to describe the regime transitions:

$$\mathrm{P}\,(s_t = \mathrm{i}\,|\,s_{t-1} = \mathrm{j}\,) = \mathrm{P}_{ij} = \begin{bmatrix} \mathrm{p}_{00} & \mathrm{p}_{01} \\ \mathrm{p}_{10} & \mathrm{p}_{11} \end{bmatrix} \qquad (2)$$

where P_{ij} is the probability of transitioning from regime j at time $t-1$ to regime i at time t.

4.2. Mixed-Asset Portfolio Analysis

As a second step in the research, we assess the role of SRE in a mixed-asset portfolio under varying market conditions. We first identify macroeconomic regimes by applying a Markov regime-switching model to quarterly nominal U.S. GDP data. To meet the model's assumption of stationarity, we preprocess the data by taking the logarithm of the GDP series followed by the computation of its second difference. To reduce the influence of extreme observations, we apply a Winsorization procedure by capping the transformed series at the 1st and 99th percentiles. We then iteratively estimate a two-state Markov regime-switching model using a 40-quarter rolling window and moving it by one quarter at a time throughout the sample. Within each iteration, we estimate the regime for the following quarter based on the transition probabilities obtained from historical data only. This ensures the forward-looking nature of the regime classification. Alternatively, we identify VIX-based regimes using the same Markov regime-switching framework, but applied to the U.S. VIX index at a monthly frequency.[4] We transform the series by taking the first difference of the VIX level and Winsorize the resulting observations at the 1st and 99th percentiles. We then estimate the model using a 120-month rolling window, the monthly analogue of the 40-quarter GDP rolling window.

We then implement a regime-switching portfolio backtest, with the optimization criterion shifting according to the estimated regimes. Specifically, during low-risk periods, we apply a maximum Sharpe ratio approach to reflect investor preference for higher returns in favorable economic conditions. Conversely, during high-risk periods, we switch to a minimum variance approach, prioritizing risk reduction during periods of market turbulence. To ensure a realistic investment framework, we use a 36-month rolling window of historical data to estimate expected returns, volatilities, and the covariance matrix of asset returns. The financial asset (i.e., stocks, bonds, and securitized real estate) allocations are rebalanced quarterly (monthly for the VIX-based strategy), while that of direct real estate is rebalanced once every three years only to reflect its illiquidity and high transaction costs. Asset allocation decisions for each period rely solely on data available at the

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[4] Using VIX at a lower frequency, such as quarterly, can mask short-term market shifts and thereby affect the resulting regime classifications. In particular, aggregation may smooth the series and reduce the variation that VIX is designed to capture.

end of the preceding period. For financial assets, we consider transaction costs of 10 basis points (bps), consistent with estimates for investors trading index-tracking ETFs (Bulla *et al.,* 2011; Hoesli *et al.,* 2025; Ledoit and Wolf, 2025). For direct real estate, we assume transaction costs of 150 bps to capture the substantially higher fees of property transactions. This assumption is in line with the average cost reported for U.S. pension funds investing in private real estate and represents the overall investment cost for the asset class (Carlo *et al.*, 2021; Johner and Hoesli, 2025). The backtesting period is from 2003 to 2024. The first 36 months (2000-2002) are used to construct the estimation window, during which the portfolio drifts passively until rebalancing begins.

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

$$\max_{w} SR_{p,w} = \max_{w} \frac{R_{p,w} - R_f}{\sigma_{p,w}} \tag{3}$$

where $SR_{p,w}$ is the Sharpe ratio of portfolio p with weights w, $R_{p,w}$ is the return of portfolio p with weights w computed using the vector of returns R, R_f is the risk-free rate. The minimum variance optimization is expressed as:

$$\min_{w} \sigma_{p,w} \tag{4}$$

Both optimizations are subject to the same constraints, namely that the portfolio weights be positive and sum to one. The standard deviation $\sigma_{p,w}$ of each portfolio p with weights w is derived using the returns covariance matrix.

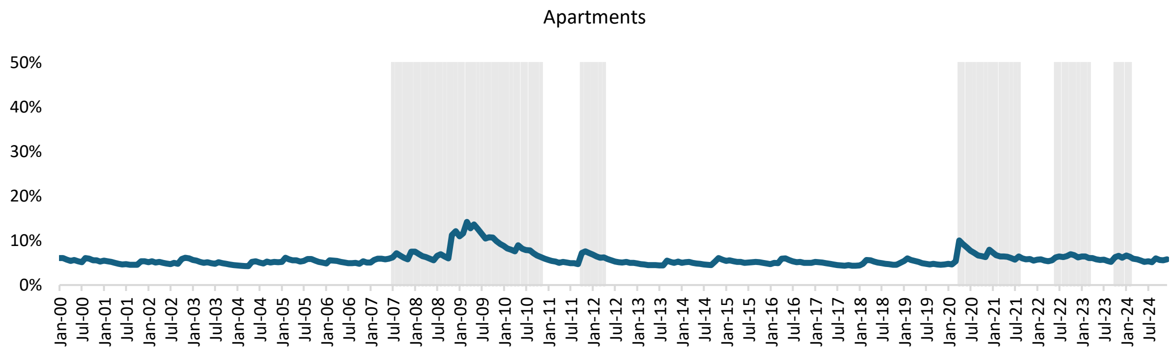
Given our interest in examining both SRE as an aggregate asset class and the optimal composition of the SRE bucket depending on market conditions, we consider four portfolio compositions: (1) stocks, bonds, and direct real estate fixed at 10%, (2) stocks, bonds, direct real estate fixed at 10%, and securitized real estate as a single aggregate asset class, (3) stocks, bonds, direct real estate fixed at 10%, and securitized real estate broken down by sector (without caps), and (4) stocks, bonds, direct real estate fixed at 10%, and securitized real estate broken down by sector (10% cap per sector). As outlined above, we consider a fixed 10% target weight for direct real estate, consistent with institutional practice (PREA, 2025). This level provides sufficient exposure to capture the diversification benefits of the asset class, while remaining low enough to limit illiquidity risk. Furthermore, imposing a 10% limit on individual SRE sectors helps to control potential concentration risk by preventing any single sector from dominating the portfolio allocation at a time, while limits of 5 and 15% are used for robustness checks. In addition to considering a base case allocation of 10% to DRE, we also examine alternative DRE allocations of 0%, 5%, 15%, and 20%. Of particular interest is to see how the impact of holding SRE on portfolio performance and asset allocations changes when no allocation to DRE is considered. Finally, we impose a maximum cap of 50% on stocks to assess the sensitivity of the results to equity concentration.

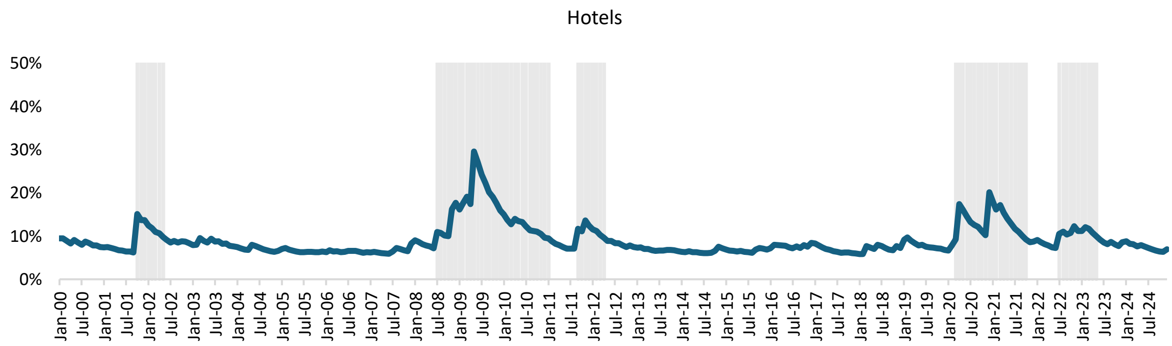
In this context, our objectives are as follows. First, we assess performance and optimal asset allocations of portfolios constructed both without and with SRE. To this end, we implement regime-switching strategies that alternate between a maximum Sharpe ratio and minimum variance approaches to capture investor preferences under different market conditions. The GDP-based strategy, our primary specification, represents a stable macroeconomic benchmark that aligns well with the long-term horizon typical of institutional investors. We complement this strategy by introducing VIX-based regimes to capture higher-frequency shifts in investor risk perception driven by market sentiment and information flow. Second, we compare the results of the regime-switching strategies with those of the portfolios constructed without regime-switching (i.e., relying on either a maximum Sharpe ratio or minimum variance approach throughout the entire period). This makes it possible to gauge the usefulness of dynamic strategies over static ones. In addition, we examine how allocations to traditional asset classes (i.e., stocks and bonds) shift across regimes. Together, this framework evaluates both the potential benefits of including SRE in mixed-asset portfolios and the impact of considering macroeconomic and market-based regimes on portfolio performance and asset allocations across long- and short-term investment horizons.

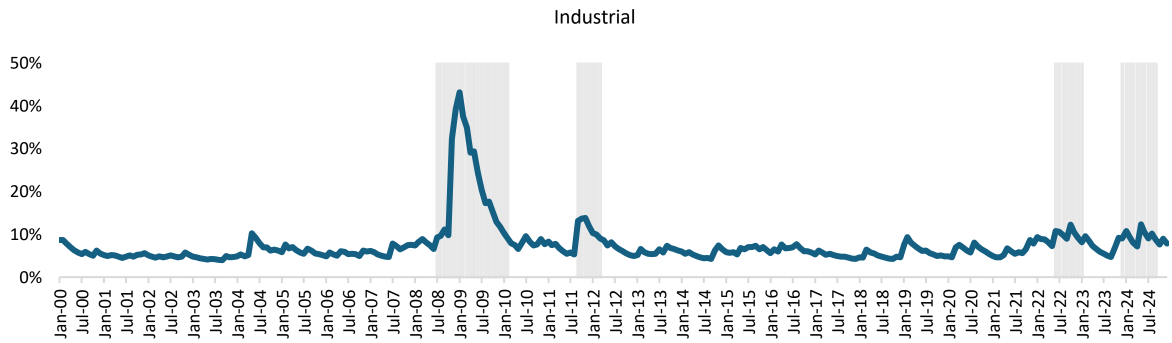
5. Results

5.1. Time-Varying Volatility of Securitized Real Estate Returns

Based on the analysis of the ACFs and PACFs, we specify the ARMA-GARCH models as follows: AR(0)-GARCH(1,1) for offices, retail, healthcare, self-storage, commercial financing, home financing, and stocks, and AR(2)-GARCH(1,1) for apartments, hotels, and industrial. Figure 2 depicts the conditional volatility and the volatility regimes for the five traditional SRE sectors (i.e., apartments, hotels, industrial, office, and retail). Overall, results indicate that the high volatility regime during the GFC persists longer than during the COVID-19 pandemic. We also see that the responses to both shocks vary across sectors. During the GFC, the industrial sector exhibited the highest volatility, whereas during COVID, volatility was the most pronounced in the retail sector, followed by hotels and office properties. These findings align with the various impacts of the shocks. The disruption caused by the 2008-2009 crisis had pronounced effects on the logistics sector, which is particularly sensitive to fluctuations in cross-border flows and global supply chain dynamics. In 2020, the retail sector suffered due to the strict quarantine measures, store closures, and the accelerated shift to e-commerce, while the office sector experienced significant disruption due to the widespread adoption of work-from-home policies (Balemi *et al*., 2021; Hoesli and Malle, 2022). Meanwhile, hotels were severely affected by travel restrictions, resulting in low occupancy rates and revenue losses. During the post-2022 period, we observe moderate increases in volatility across most sectors, although these remain smaller than those recorded during the GFC or the pandemic. The apartment sector remains the most resilient, underpinned by sustained housing demand and a relatively lower sensitivity to interest rate increases compared with other commercial real estate asset classes. The office sector shows the most prolonged high-volatility phase, reflecting continued uncertainty around occupancy, as hybrid-work patterns persist. Retail, in contrast, displays only a short-lived volatility spike, consistent with the initial surge in interest rates and a temporary slowdown in consumer spending.







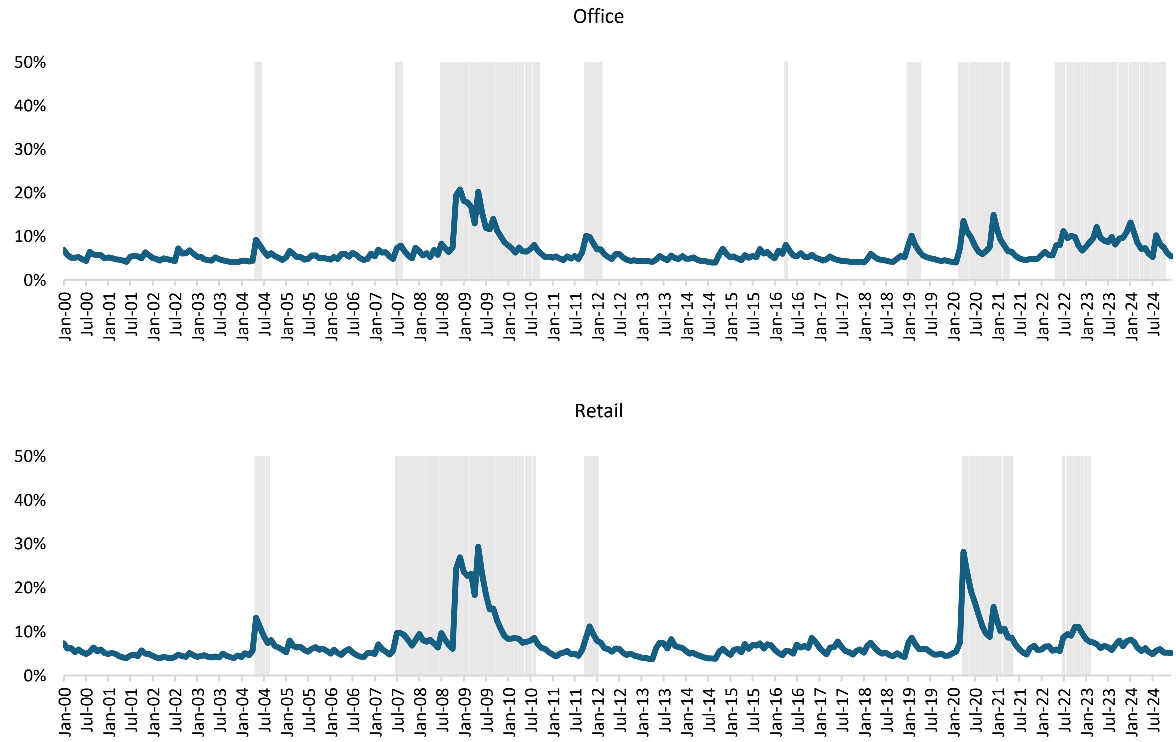


Figure 2. Volatility and Volatility Regimes of Traditional Securitized Real Estate Sectors.

Sources: NAREIT 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.

Figure 3 illustrates the conditional volatility and the volatility regimes for the two alternative SRE sectors (i.e., healthcare and self-storage). The healthcare sector exhibited a noticeable but short-lasting volatility spike during the COVID-19 pandemic, whereas the high-volatility phase was more prolonged during the GFC. While the pandemic was primarily a healthcare crisis, the sector remained relatively stable, compared to retail and hotels, reflecting the continued demand for medical facilities. Following 2022, the sector shows only mild increases in volatility, consistent with its defensive characteristics. In contrast, the self-storage sector emerges as mostly resilient (similar to apartments), with no extreme volatility spikes throughout the entire period. This stability likely results from the continued need for storage solutions during periods of distress, as businesses and individuals adjust to closures and relocations, although small post-2022 volatility fluctuations may coincide with slower household mobility. Furthermore, it can be assumed that investors have historically exhibited less speculative behavior toward these asset classes, which may partly explain their more limited post-2022 adjustments.

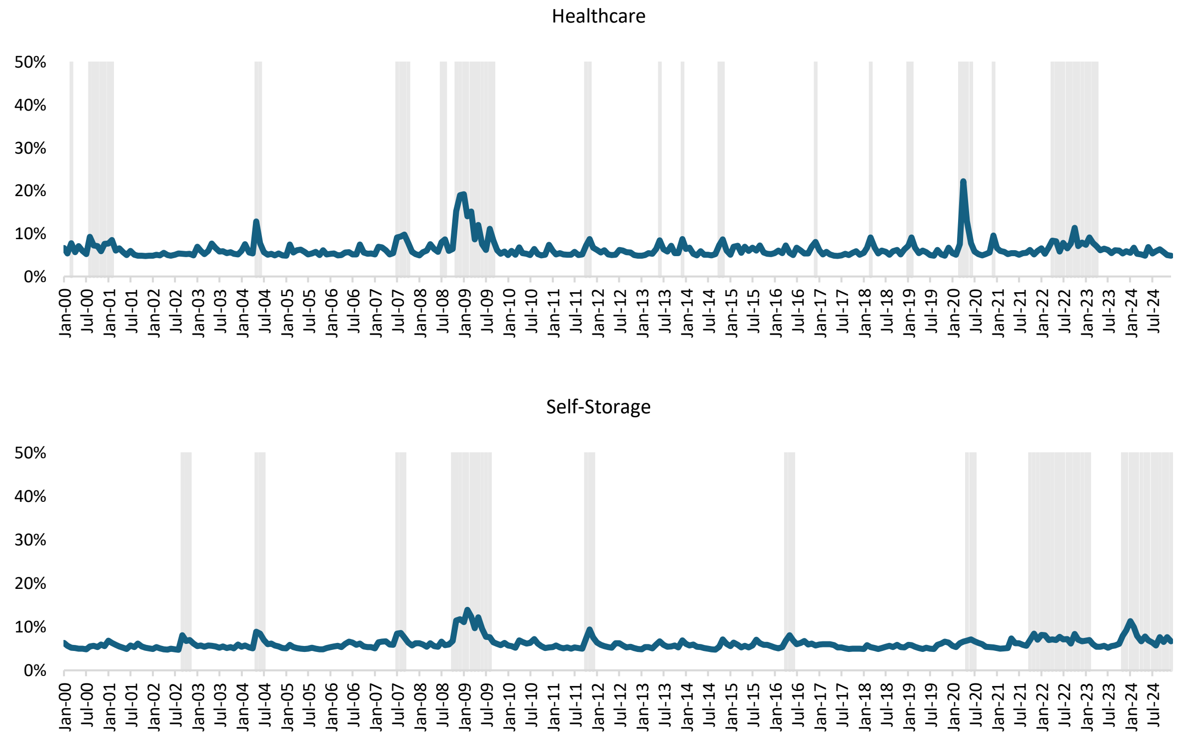


Figure 3. Volatility and Volatility Regimes of Alternative Securitized Real Estate Sectors.

Sources: NAREIT 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.

Finally, Figure 4 presents the conditional volatility and the volatility regimes for the two types of mortgage REITs (i.e., commercial financing and home financing).[5] Commercial financing REITs experienced a prolonged high-volatility regime during the GFC, reflecting widespread defaults and tightening credit conditions. During the COVID-19 period, these REITs exhibited a short-lived but intense volatility spike, likely driven by high uncertainty and short-term liquidity concerns. In contrast, home financing REITs exhibited relatively low volatility during the GFC, as lower interest rates and government support helped to stabilize the housing market. However, during the pandemic, these REITs experienced a more pronounced volatility spike. This can be attributed to uncertainties about households' ability to pay their mortgages due to concerns regarding employment and income stability, as well as uncertainty regarding the long-term effects of remote work on the housing market (Duca *et al.*, 2021). During the most recent period, both commercial and home-financing REITs exhibited renewed volatility increases associated with the rise in interest rates. The spike was more

[5] Appendix 4 shows volatility and volatility regimes of the SRE aggregate index and stocks.

pronounced for home-financing REITs, while commercial financing REITs showed a more prolonged but less intense volatility pattern.

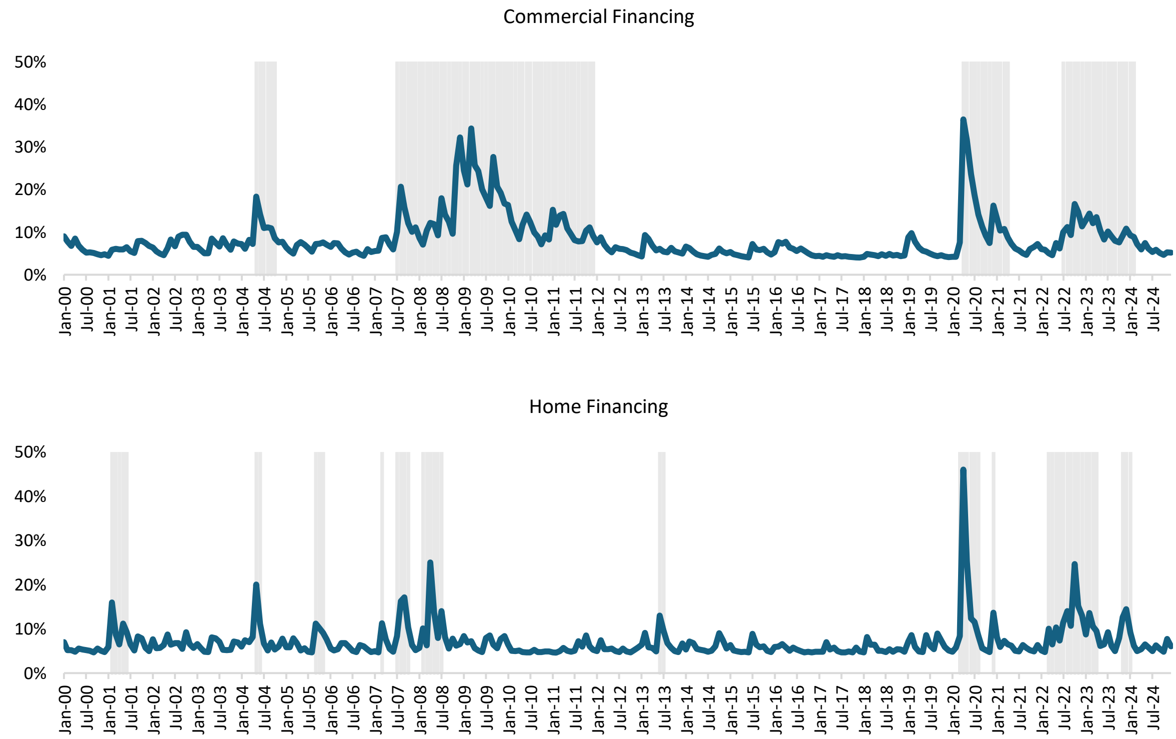


Figure 4. Volatility and Volatility Regimes of Mortgage REITs.

Sources: NAREIT 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.

Overall, we find that sectoral responses to the GFC and the COVID-19 pandemic differ, with the self-storage, apartment, and healthcare sectors being the most resilient, likely due to the robust nature of their services. Self-storage properties benefited from continued demand driven by residential mobility, apartments remained supported by housing needs, while the healthcare sector proved defensive due to its critical role in society. In contrast, other sectors experienced sharper and more prolonged volatility. Notably, the high-volatility regime during the GFC was more persistent than that during the pandemic, reflecting the more systemic nature of the crisis. While less sharp than previous crises, the post-2022 phase marks a transition to a new environment with higher interest rates and increased inflation. This is a result of growing geopolitical instability, which led to a significant downward revision of real estate asset values and dampened investors' outlook. Volatility increased across most sectors, with mortgage and office REITs showing the strongest reactions, while healthcare, self-storage, and apartment sectors were the most stable.

5.2. Mixed-Asset Portfolio Analysis

This section presents the results of our mixed-asset portfolio analyses, focusing on both performance and asset allocations. We first evaluate the performance of the portfolios constructed both without SRE and with SRE and compare sector-based SRE portfolios with those incorporating an aggregate SRE index. We also assess the added value of GDP- and VIX-based regime-switching frameworks relative to standard maximum Sharpe ratio and minimum variance strategies. We then examine portfolio asset allocations, highlighting how exposures to DRE, SRE, stocks, and bonds vary across the four strategies and four portfolio compositions. Overall, the analyses emphasize the potential benefits of including SRE, particularly at the sector level, in mixed-asset portfolios and the impact of considering macroeconomic and market-based regimes on portfolio performance and asset allocations across long- and short-term investment horizons.

Table 3 displays performance metrics. First, the inclusion of SRE improves risk-adjusted performance across all strategies. For example, for the maximum Sharpe ratio strategy, adding an aggregate SRE index increases the Sharpe ratio from 0.59 to 0.67 compared to a baseline portfolio without SRE. Similarly, for the GDP-based regime-switching strategy, the Sharpe ratio rises from 0.62 to 0.71 when SRE is included (from 0.60 to 0.68 for the VIX-based strategy). For the minimum variance strategy, the inclusion of SRE, either aggregate or with sectors, increases returns without materially increasing risk. Second, sector-based strategies outperform those relying on an aggregate SRE index, though managing concentration risk is important.[6] The effect is most pronounced within the minimum variance approach, with the Sharpe ratio increasing from 0.50 for the aggregate SRE to 0.60 for the sector-based approach. Under the maximum Sharpe ratio strategy, the uncapped sector-level SRE portfolio has a Sharpe ratio of 0.40, much lower than 0.67 for the aggregate SRE portfolio. Indeed, the capped sector-level SRE portfolio achieves only a slightly higher Sharpe ratio (0.68) than the portfolio with SRE as an aggregate.

Third, the regime-switching framework generally outperforms the static strategies on a risk-adjusted basis. This is particularly true for the GDP-based setup, while for the VIX-based strategy,

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[6] The only exception under a 10% sector limit is the VIX-based regime-switching strategy. In this case, the Sharpe ratio is higher than the baseline portfolio but lower than the portfolio with the SRE aggregate index, suggesting that a 10% cap is not sufficiently tight to fully mitigate the concentration risk issue under monthly rebalancing. Appendix 5 presents sensitivity results for the VIX-based regime-switching strategy using alternative sector limits (no cap, 5%, 10%, and 15%). Under a 5% cap, the sector-level SRE portfolio becomes the best-performing VIX specification, whereas a looser 15% cap performs worse than the base case 10% cap.

performance is more sensitive to the sector caps. The GDP-based regime-switching strategy with sector-level SRE capped at 10% achieves the highest Sharpe ratio (0.72), compared with 0.68 for the maximum Sharpe ratio approach. In contrast, under a 10% cap, the VIX-based regime-switching strategy underperforms the maximum Sharpe ratio approach, consistent with greater concentration risk in a more actively rebalancing setting. Indeed, under a tighter 5% sector cap, this strategy obtains the highest Sharpe ratio (0.71). Overall, the VIX-based strategy shows slightly lower performance than the GDP-based strategy. One potential explanation is that VIX-based regimes are more sensitive to short-term market dynamics, which can lead to more frequent regime changes, less stable allocations, and lower performance.

Table 3. Performance Metrics for Various Strategies and Portfolio Compositions.

	Minimum Variance Strategy			
	No SRE	SRE Agg.	SRE Sect. (No Cap)	SRE Sect. (10% Cap)
Return (%)	4.36	4.74	5.81	5.79
Risk (%)	5.78	5.86	6.70	6.69
Sharpe Ratio	0.44	0.50	0.60	0.60
	Maximum Sharpe Ratio Strategy			
	No SRE	SRE Agg.	SRE Sect. (No Cap)	SRE Sect. (10% Cap)
Return (%)	6.03	6.79	6.15	7.88
Risk (%)	7.13	7.48	10.85	8.90
Sharpe Ratio	0.59	0.67	0.40	0.68
	GDP-Based Regime-Switching Strategy			
	No SRE	SRE Agg.	SRE Sect. (No Cap)	SRE Sect. (10% Cap)
Return (%)	5.94	6.77	6.71	7.46
Risk (%)	6.70	6.97	8.82	7.83
Sharpe Ratio	0.62	0.71	0.56	0.72
	VIX-Based Regime-Switching Strategy			
	No SRE	SRE Agg.	SRE Sect. (No Cap)	SRE Sect. (10% Cap)
Return (%)	5.66	6.40	5.94	6.95
Risk (%)	6.42	6.83	9.18	8.08
Sharpe Ratio	0.60	0.68	0.45	0.64

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

For our GDP-based regime-switching strategy, Figure 5 presents the 36-month rolling Sharpe ratios of portfolios with SRE relative to the baseline portfolio without SRE.[7] Before the GFC, all three

[7] Appendix 6 shows the 36-month rolling Sharpe ratios of portfolios with SRE relative to the baseline portfolio without SRE for our VIX-based regime-switching strategy.

SRE configurations contributed positively to the risk-adjusted performance, with the sector-level portfolios showing the best results. However, during the GFC, Sharpe ratios declined sharply, with the uncapped sector-level portfolio experiencing the most pronounced drop. During the most recent period, the capped sector-level portfolio delivered some Sharpe ratio improvements, whereas the uncapped portfolio again exhibited a noticeable decline. The SRE aggregate portfolio maintains a near-zero Sharpe ratio relative to the baseline portfolio without SRE for most of the post-GFC period, although it shows a positive phase from 2013 to 2016. Overall, this is consistent with a limited allocation to SRE aggregate following the GFC.

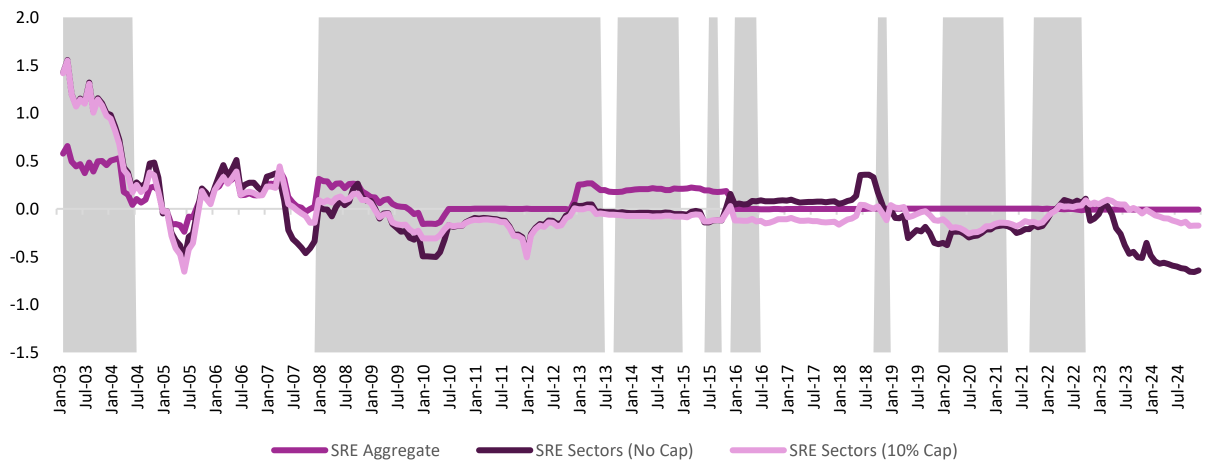

Figure 5. Rolling Difference of Sharpe Ratios of Regime-Switching Portfolios with SRE minus Sharpe Ratios of Portfolios without SRE, and GDP Regimes, 2003-2024.

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Notes: Stable market periods are in white, while volatile market periods are in grey.

We then focus on the portfolio that achieved the highest Sharpe ratio (i.e., the GDP-based regime-switching strategy with capped sector-level SRE) and examine the impact of alternative DRE target allocations on performance (Table 4). The results show that higher DRE allocations are associated with stronger risk-adjusted performance, with the Sharpe ratio increasing to 0.85 when the DRE weight is set at 20%. Conversely, when no DRE allocation is considered, SRE cannot fully substitute for its performance contribution, and the Sharpe ratio declines to 0.61 compared with 0.72 for the baseline case with a 10% DRE weight.

Table 4. Performance Metrics for the GDP-Based Regime-Switching Strategy with Sector-Level SRE Capped at 10% for Various DRE Target Allocations.

	No DRE	DRE 5%	DRE 10%	DRE 15%	DRE 20%
Return (%)	7.31	7.34	7.46	7.57	7.68
Risk (%)	9.00	8.40	7.83	7.38	6.96
Sharpe Ratio	0.61	0.66	0.72	0.78	0.85

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Figure 6 shows average portfolio allocations for our four strategies and four portfolio compositions.[8] Corporate bonds generally have the largest allocations (16-53%), while government bonds remain stable at 22-27% across strategies. The high allocation to corporate bonds compared to government bonds is consistent with the risk-return characteristics of these asset classes. As shown in the summary statistics (Table 1), investment-grade corporate bonds deliver higher average annual returns (4.97%) compared to 10-year government bonds (3.96%) while exhibiting slightly lower risk (6.25% vs. 7.61%, respectively). The allocation to stocks ranges from 10% to 32% and depends on whether SRE is included or not in the portfolio (i.e., a larger allocation to SRE coincides with a lower allocation to stocks, and inversely). This is particularly true for the portfolio compositions with SRE disaggregated by sectors.

[8] Appendix 7 shows average SRE mixed-asset portfolio allocations across sectors for our four strategies, 2003-2024.

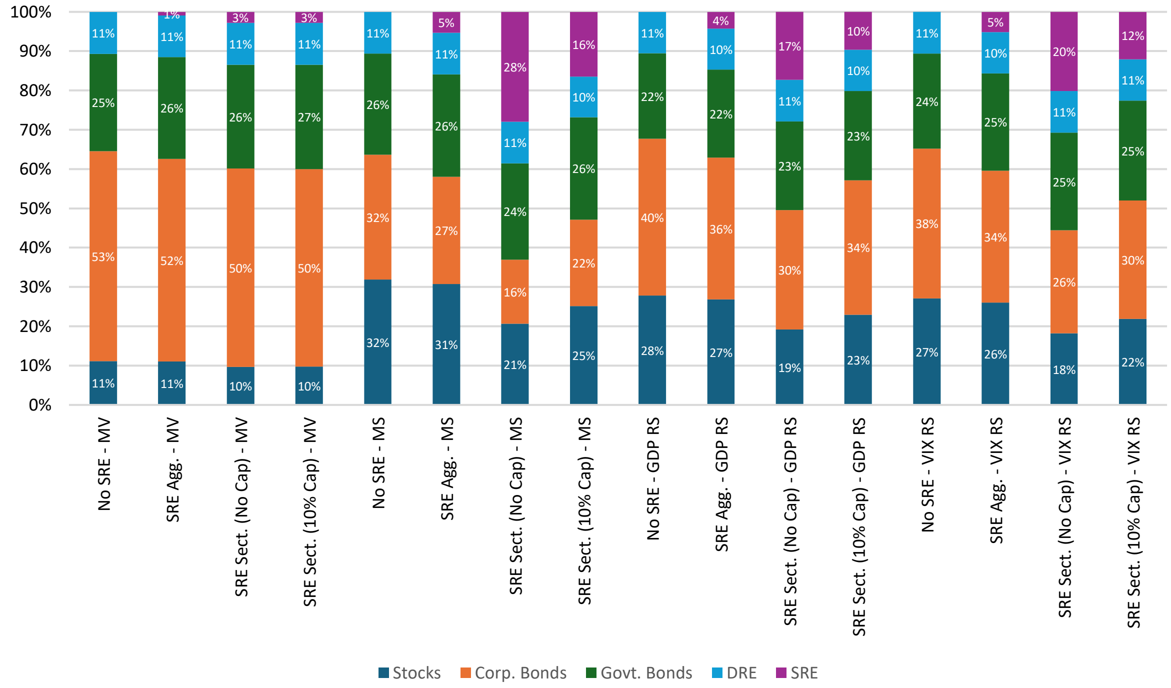

Figure 6. Average Mixed-Asset Portfolio Allocations, 2003-2024.

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Notes: MV = Minimum Variance Strategy, MS = Maximum Sharpe Ratio Strategy, GDP RS = GDP-Based Regime-Switching Strategy, and VIX RS = VIX-Based Regime-Switching Strategy.

Across all strategies and portfolio compositions, the average allocation to direct real estate remains close to the fixed 10% target, ranging between 10.41% and 10.66%. The minimum weights, between 7.49% and 8.37%, occur mainly from late 2010 to mid-2011 during the post-GFC recovery, while the maximum weights, ranging from 13.34% to 14.68%, correspond to late 2022 and, in a few cases, late 2023, likely reflecting relative resilience in the real estate market alongside weaker performance of stocks and bonds during the period.

The inclusion of sector-level SRE increases the portfolio's real estate exposure compared to the aggregate SRE allocation, with the effect being most pronounced for the maximum Sharpe ratio strategy. In contrast, minimum variance portfolios allocate only a marginal share (1-3%) to SRE, regardless of whether it is included in aggregate or by sector. Imposing a 10% cap on individual SRE sectors results in more balanced allocations. Under capped conditions, the allocation to sector-level SRE ranges from 3% (minimum variance strategy) to 16% (maximum Sharpe ratio strategy), while it is from 3% to 28% for uncapped portfolios.

As would be expected, the asset weights for both regime-switching strategies are intermediate to those for the minimum variance and maximum Sharpe ratio strategies. Consequently, the regime-switching setup produces the most diversified portfolios, with a more balanced distribution of weights across stocks, bonds, and SRE. In this framework, the allocation to SRE is 4-5% when the aggregate index is considered, 17-20% with the uncapped sectors, and 10-12% when the sectoral weights are capped. As the most defensive strategy, the minimum variance approach contains large allocations to bonds and limited allocations to stocks. The largest allocations to SRE are for the maximum Sharpe ratio strategy.

Figure 7 presents the portfolio compositions over time for a GDP-based regime-switching strategy.[9] In the baseline portfolio composition without SRE, asset allocations shift markedly between stocks and bonds, with a notable increase in government bonds during periods of distress (i.e., the GFC and the COVID-19 pandemic). It is worth noting that during the post-GFC period, the allocation to government bonds remained predominant, much more so than in the pre-GFC period, which is consistent with the decline in long-term U.S. interest rates observed between 2010 and 2014.

Introducing an aggregate SRE index leads to a more balanced allocation, mainly during the pre-GFC period. Following the crisis, the allocation to SRE largely vanishes, with brief re-entries during 2012-2013 and in late 2022, and the asset allocations become almost identical to the baseline portfolio. When SRE is disaggregated by sector and no caps are applied, the allocations are largely concentrated in some sectors (i.e., self-storage or retail) during certain periods, likely due to their higher returns or perceived resilience in those times. This also reflects a limitation of unconstrained mean-variance optimization, which tends to favor assets with strong historical performance (Hyung and de Vries, 2007). Imposing a 10% cap per sector results in more balanced allocations.

From the second half of 2022, the regime-switching strategy in the baseline and SRE aggregate specifications allocates around 90% of the portfolio to stocks (with the remaining 10% held in direct real estate under the fixed allocation constraint).[10] This pronounced shift toward equities reflects the post-pandemic recovery in equity markets and the weakness of bonds and securitized real estate following the rise in interest rates. Notably, when SRE is disaggregated by sector, certain segments (e.g., self-storage, retail, hotels, and industrial) continue to appear in the allocations, indicating that sector-level diversification benefits persist even during equity-dominated periods.

[9] Appendices 8, 9, and 10 show the portfolio compositions over time for minimum variance, maximum Sharpe ratio, and VIX-based regime-switching strategies, respectively.

[10] Appendix 11 presents the average mixed-asset portfolio allocations for the GDP-based regime-switching strategy with a 50% cap imposed on the stock allocation. This restriction leads to a partial substitution of stocks by SRE, resulting in higher average SRE allocations.

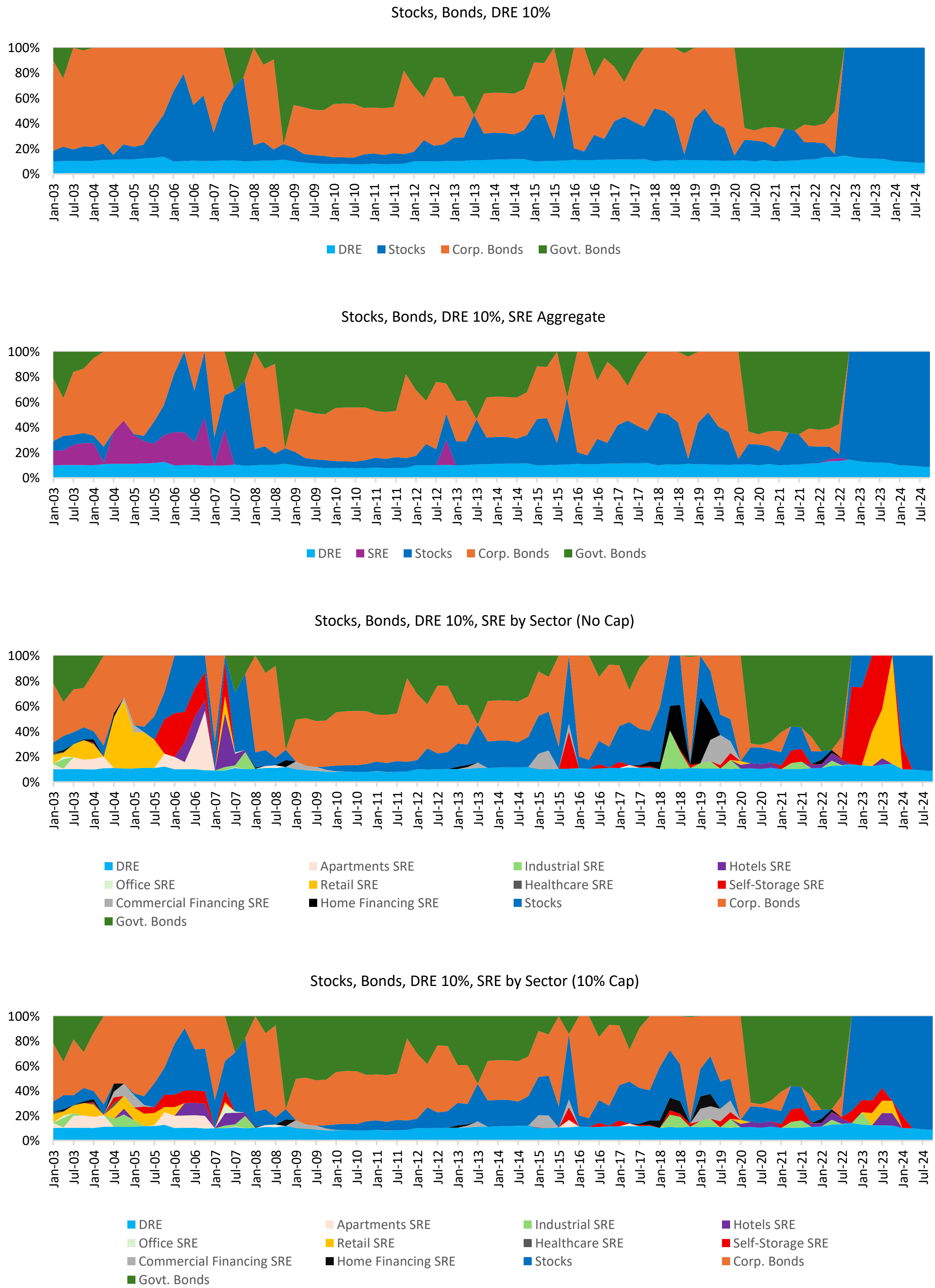

Figure 7. Portfolio Compositions over Time with GDP-Based Regime-Switching, 2003-2024.

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

6. Conclusions

This paper examines the role of SRE in a U.S. investor's mixed-asset portfolio, considering both aggregate and sector-level exposures. We analyze a 25-year period marked by four major crises: the dotcom crash, the GFC, the COVID-19 pandemic, and the recent shock in inflation and interest rates. We first show that SRE sectors respond differently to shocks, highlighting the importance of sector-level SRE exposure. Self-storage, apartment, and healthcare properties were most resilient during both the GFC and the COVID-19 pandemic, likely due to the robust nature of their services. In contrast, office, retail and hotel sectors experienced more severe drawdowns, driven by disruptions in occupancy patterns and operational models. Notably, the high-volatility regime during the GFC was more persistent than that during the pandemic, reflecting the more systemic nature of the crisis. During the post-2022 period, marked by higher interest rates and increased inflation, volatility spikes were less pronounced than during previous crises. Volatility increased across most sectors, with mortgage and office REITs showing the strongest reactions, while healthcare, self-storage, and apartment sectors remained comparatively stable.

In the context of mixed-asset portfolio performance, our findings are as follows. First, adding SRE improves risk-adjusted performance across all strategies. Under the maximum Sharpe ratio strategy, adding an aggregate SRE index raises the Sharpe ratio from 0.59 to 0.67 relative to the baseline without SRE. Similarly, under the GDP-based regime-switching framework, the Sharpe ratio increases from 0.62 to 0.71 when SRE is included. Second, sector-based strategies outperform those relying on an aggregate SRE index, though managing concentration risk is important. The outperformance is most pronounced for the minimum variance strategy, where the Sharpe ratio rises from 0.50 for the aggregate SRE to 0.60 for the sector-based configuration. Third, the regime-switching framework generally outperforms the static strategies on a risk-adjusted basis, with performance depending on the effectiveness of constraints in limiting concentration risk. Taken together, the maximum Sharpe ratio and GDP-based regime-switching approaches perform best when sectoral SRE weights are capped at 10%, with Sharpe ratios of 0.68 and 0.72, respectively. For the minimum variance strategy, the highest Sharpe ratio of 0.60 occurs both with uncapped sector weights and a 10% sector cap. In the VIX-based setup, the highest Sharpe ratio (0.71) is obtained under a 5% sector cap. Compared with the GDP-based strategy, the VIX-based strategy delivers slightly weaker performance. This likely reflects the nature of VIX-based regimes, which tend to be less persistent and more sensitive to short-term market dynamics.

In terms of portfolio compositions, the regime-switching approach yields more diversified allocations across stocks, bonds, and SRE, with asset weights that fall between those of the static strategies. With a 10% sector cap, sector-level SRE allocations range from 3% (minimum variance) to

16% (maximum Sharpe ratio), rising to 3-28% when sector weights are unrestricted. For the regime-switching strategies, average SRE allocations are moderate and slightly higher in the VIX-based setup than in the GDP-based setup. The allocations are 10% (GDP) versus 12% (VIX) under the 10% cap and 17% (GDP) versus 20% (VIX) when sector weights are unrestricted.

Overall, the results confirm the complementary roles of SRE and DRE within mixed-asset portfolios and highlight the value of sectoral diversification as well as of a dynamic approach to SRE investments. GDP-based regimes can increase portfolio resilience during turbulent periods by shifting between return-seeking and risk-aversion goals. These regimes are relatively stable and are well suited for institutional investors with longer-term horizons. In contrast, VIX-based regimes capture higher-frequency shifts in investor risk perception driven by market sentiment and information flow. Incorporating VIX-based regimes makes the framework relevant for investors with shorter-term horizons.

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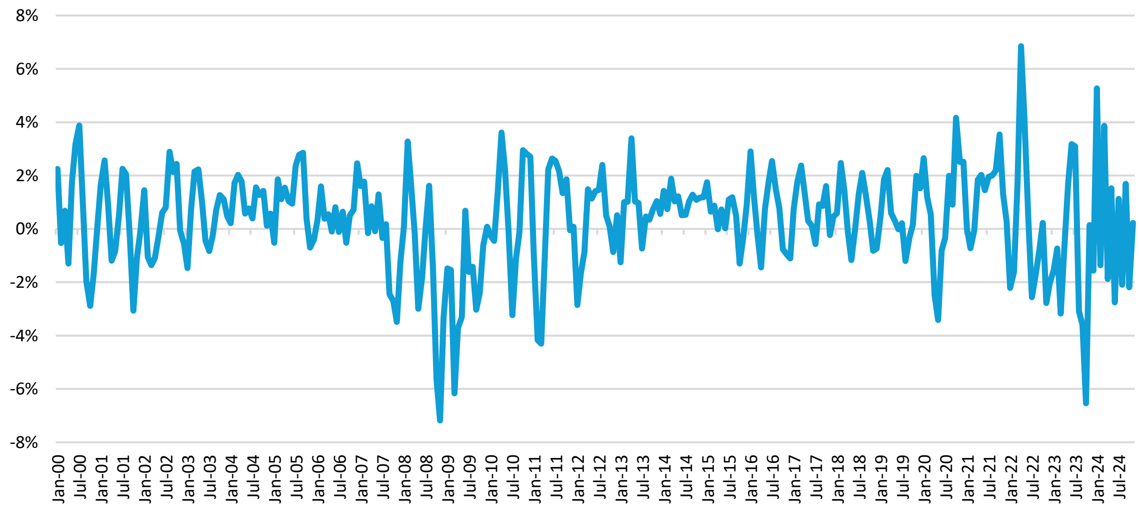
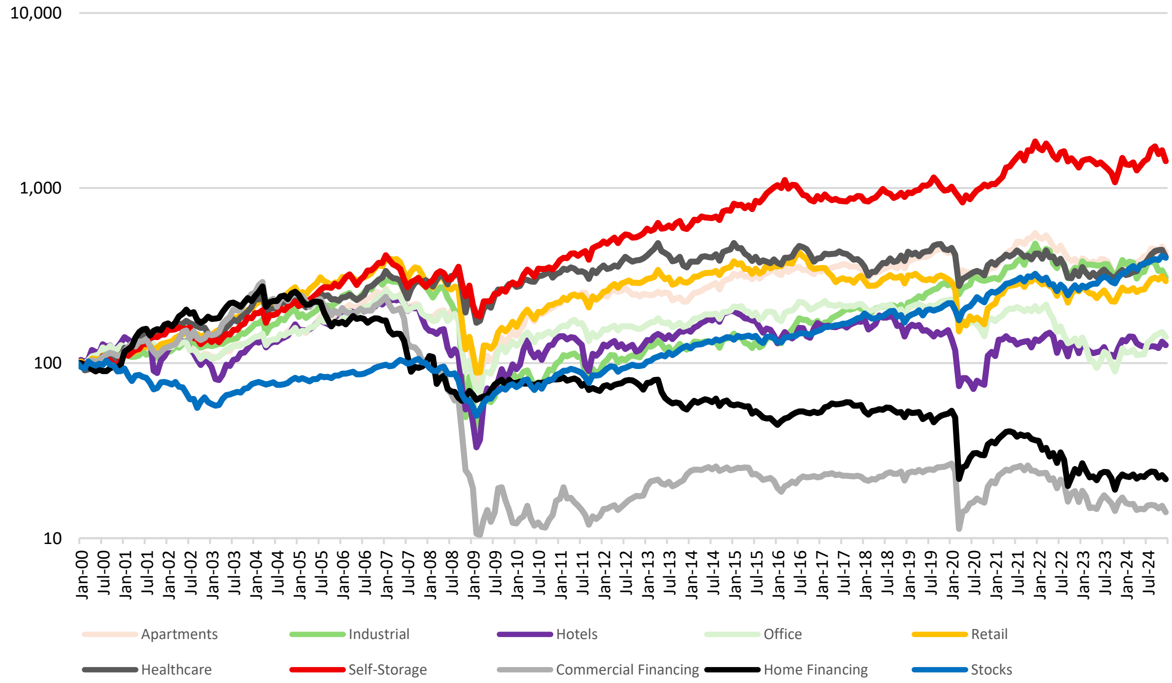
Appendix 1: Price Returns for Commercial Real Estate, 2000-2024



Sources: CoStar CCRSI and authors' calculations.

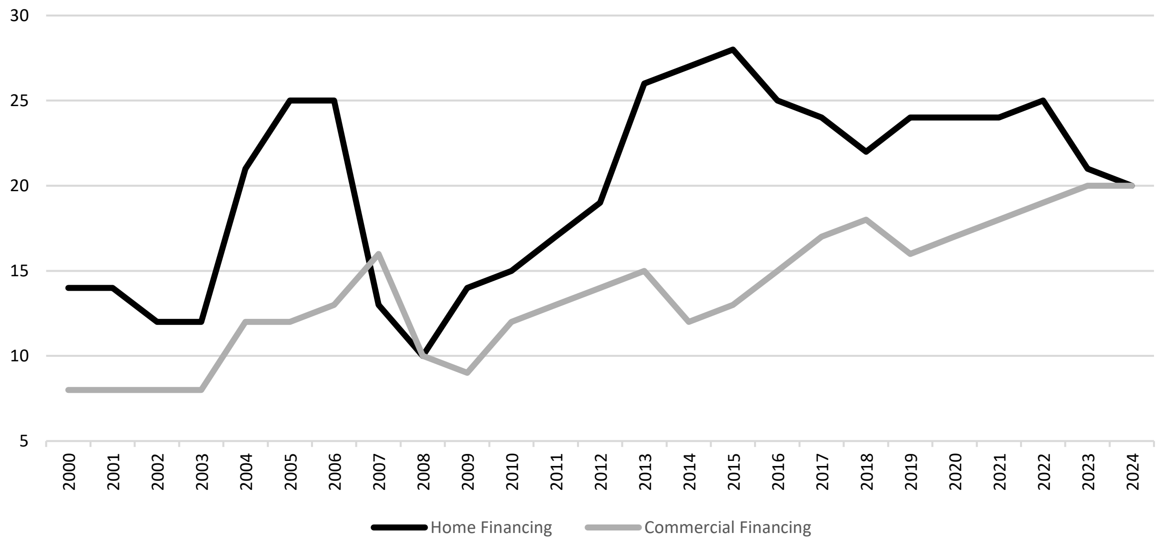
Appendix 2: Price Return Indices for SRE Sectors and Stocks



Sources: NAREIT, Bloomberg, and authors' calculations.

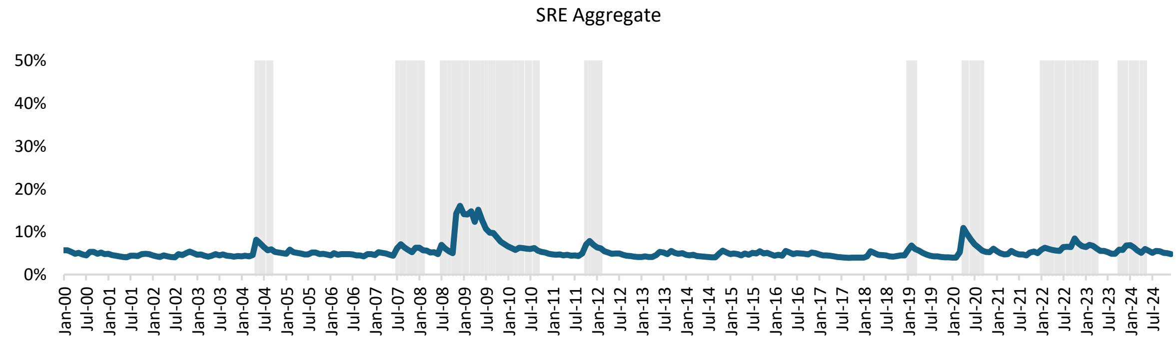
Note: The vertical axis is presented on a logarithmic scale.

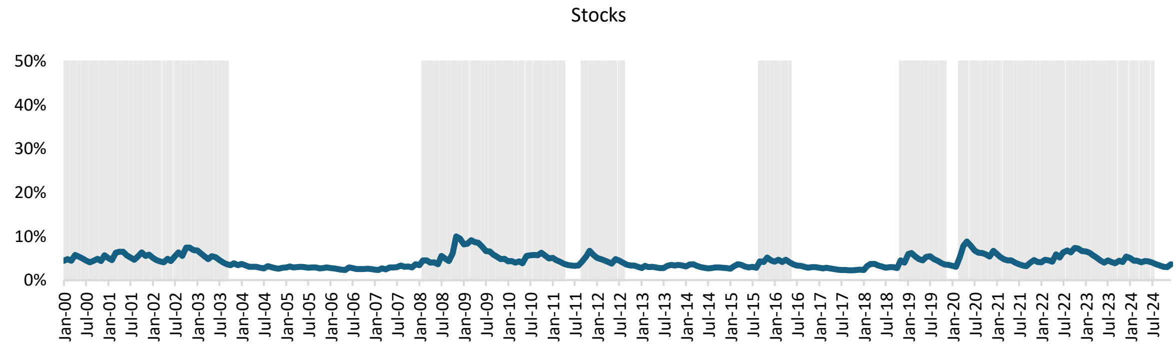
Appendix 3: Number of Mortgage REITs, 2000-2024



Sources: NAREIT and authors' calculations.

Appendix 4: Volatility and Volatility Regimes of the SRE Aggregate Index and Stocks





Sources: NAREIT, Bloomberg, and authors' calculations.

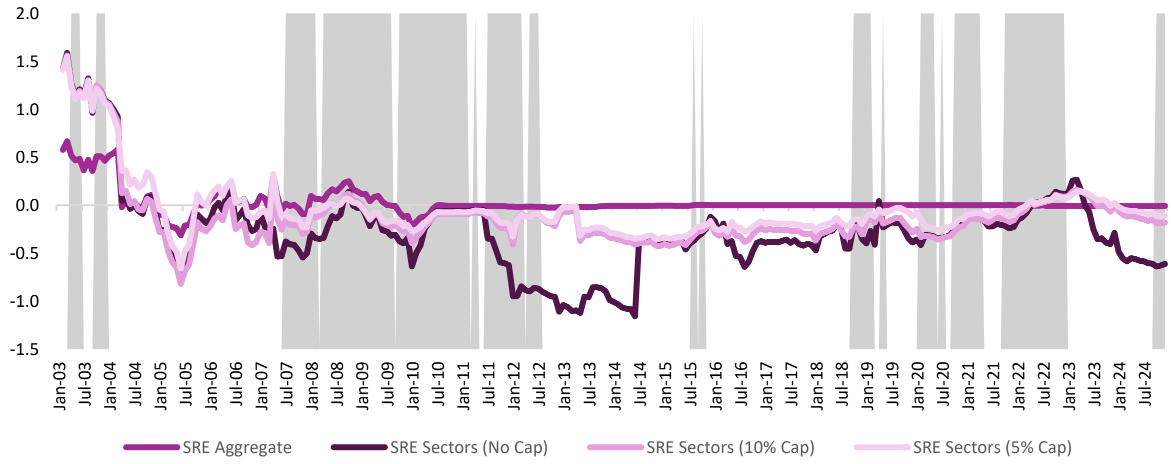
Notes: The blue line is the estimated conditional volatility. Periods of high volatility are in grey, while periods of low volatility are in white.

Appendix 5: Performance Metrics for the VIX-Based Regime-Switching Strategy Including Various SRE Sector Caps

	No SRE	SRE Agg.	SRE Sect. (No Cap)	SRE Sect. (5% Cap)	SRE Sect. (10% Cap)	SRE Sect. (15% Cap)
Return (%)	5.66	6.40	5.94	7.20	6.95	6.82
Risk (%)	6.42	6.83	9.18	7.57	8.08	8.35
Sharpe Ratio	0.60	0.68	0.45	0.71	0.64	0.60

Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

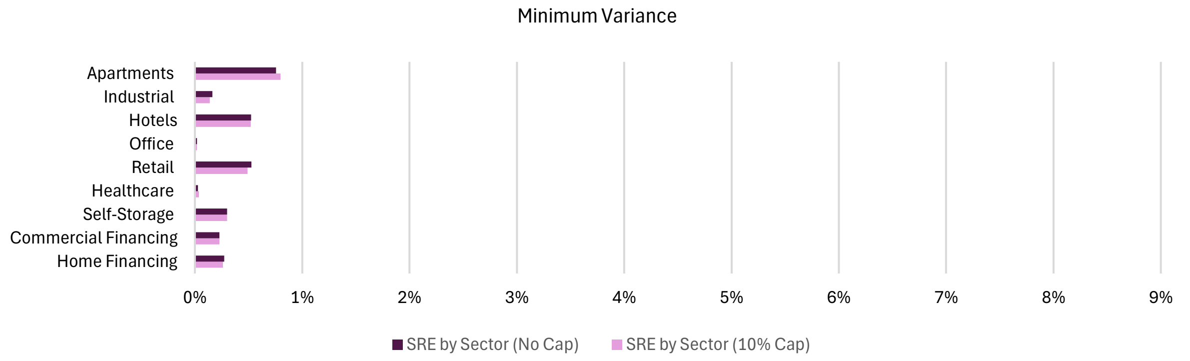
Appendix 6: Rolling Difference of Sharpe Ratios of Regime-Switching Portfolios with SRE minus Sharpe Ratios of Portfolios without SRE, and VIX Regimes, 2003-2024

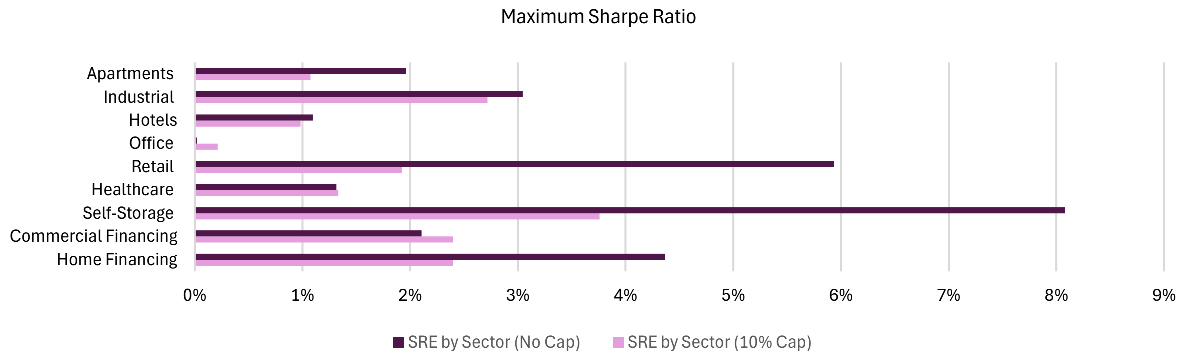


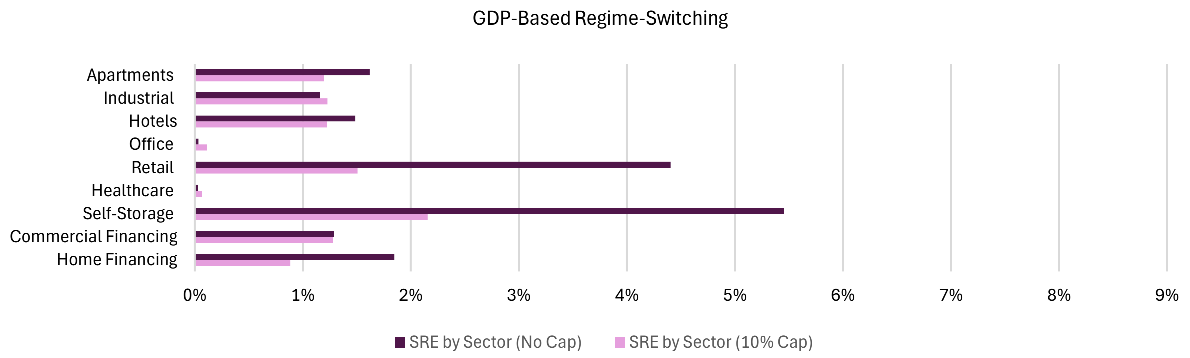
Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

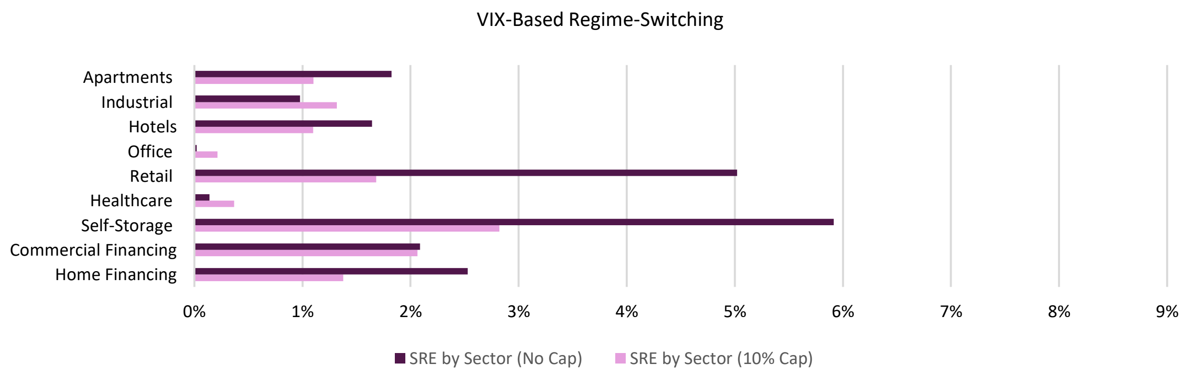
Notes: Stable market periods are in white, while volatile market periods are in grey.

Appendix 7: Average SRE Mixed-Asset Portfolio Allocations Across Sectors for Our Four Strategies, 2003-2024



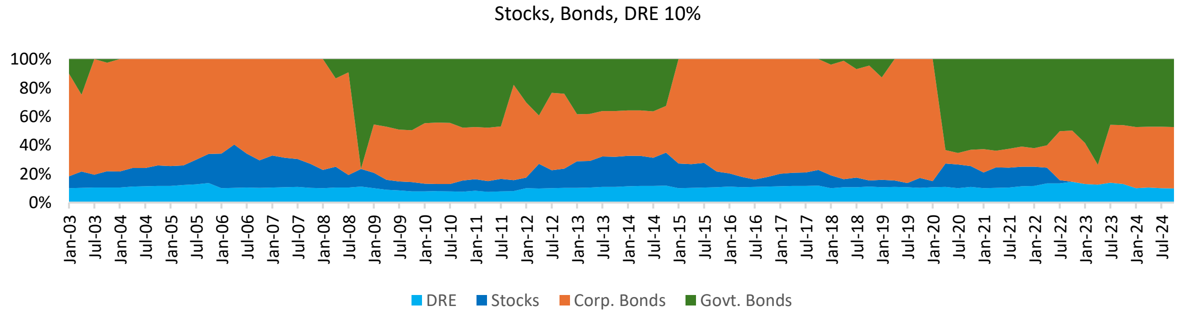


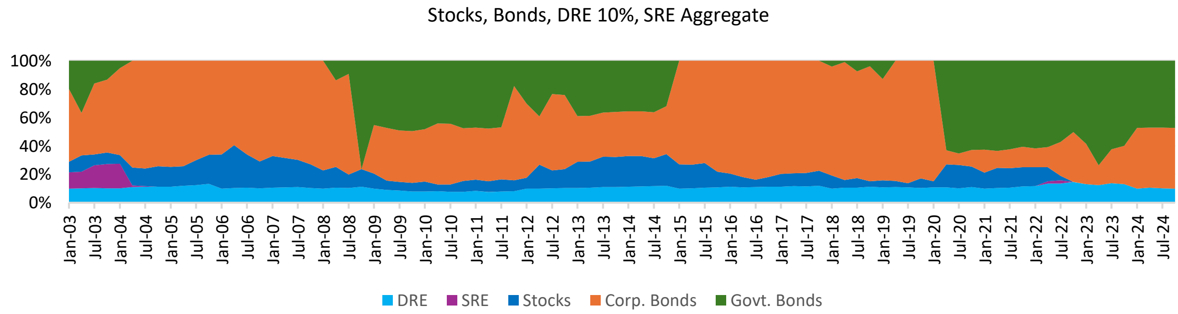


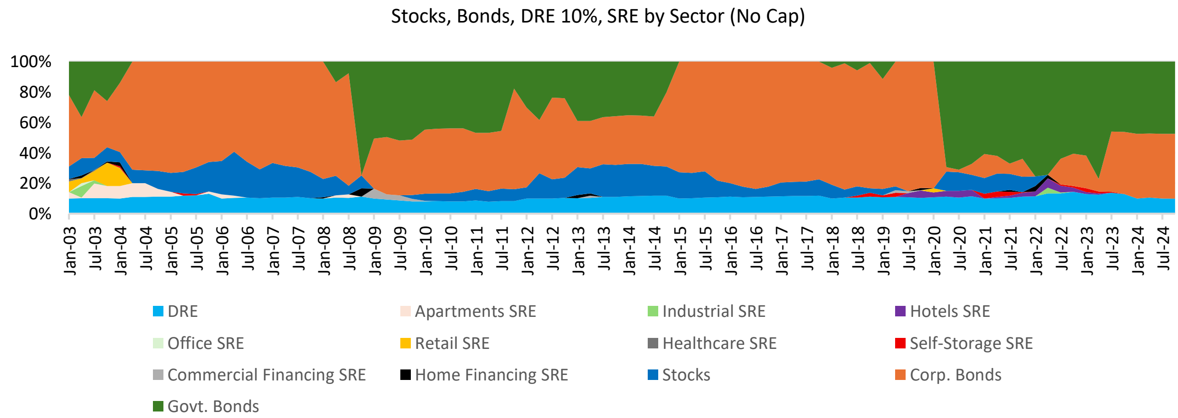


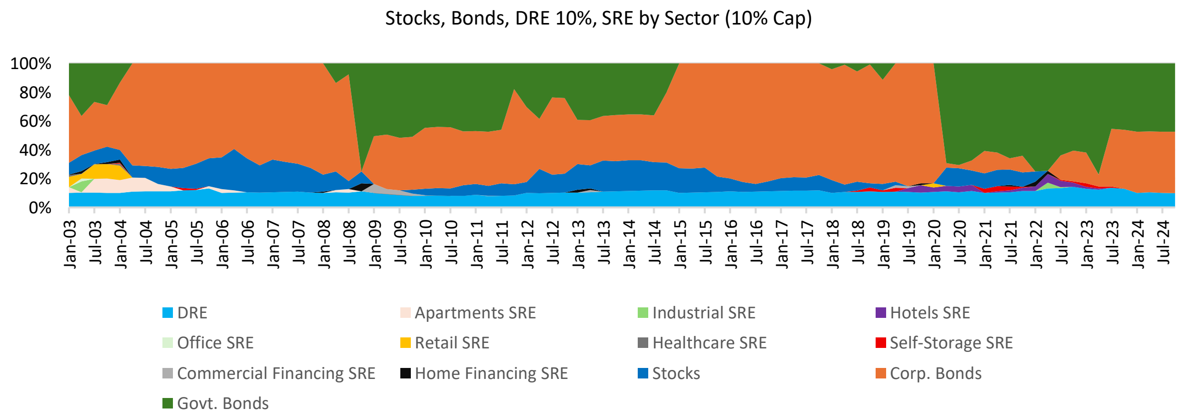
Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Appendix 8: Portfolio Compositions over Time for the Minimum Variance Strategy, 2003-2024



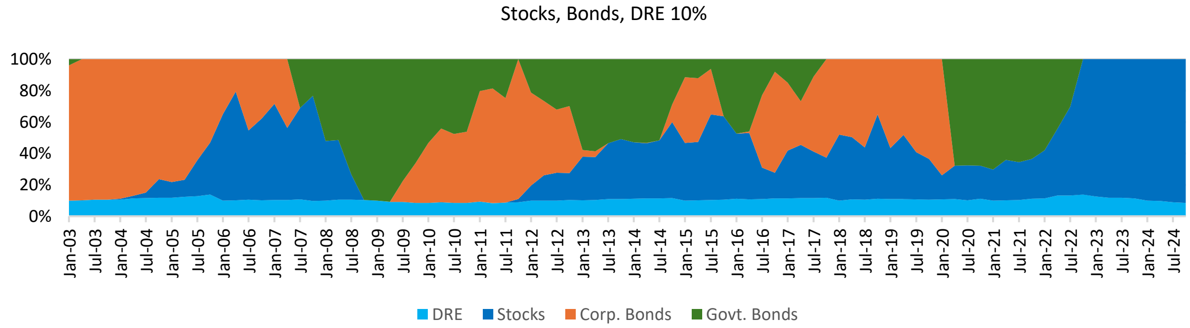


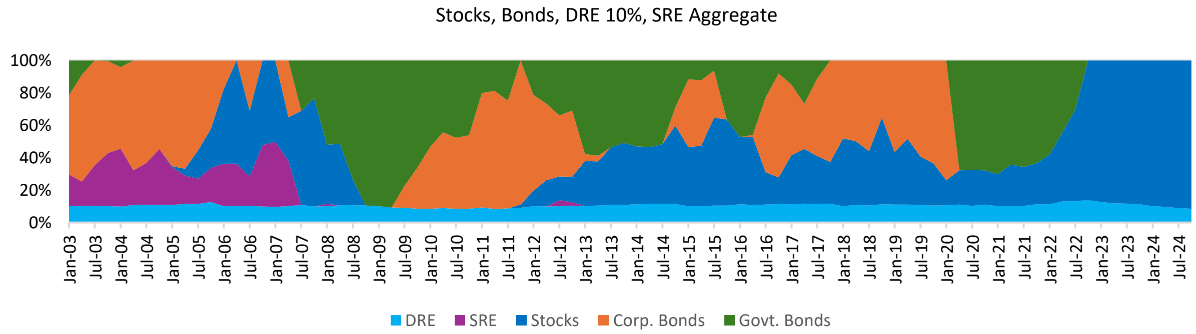


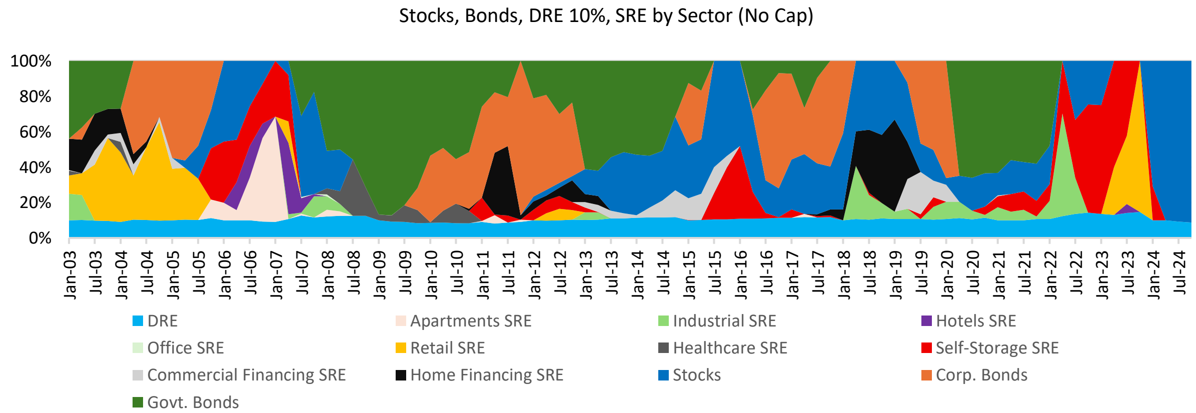


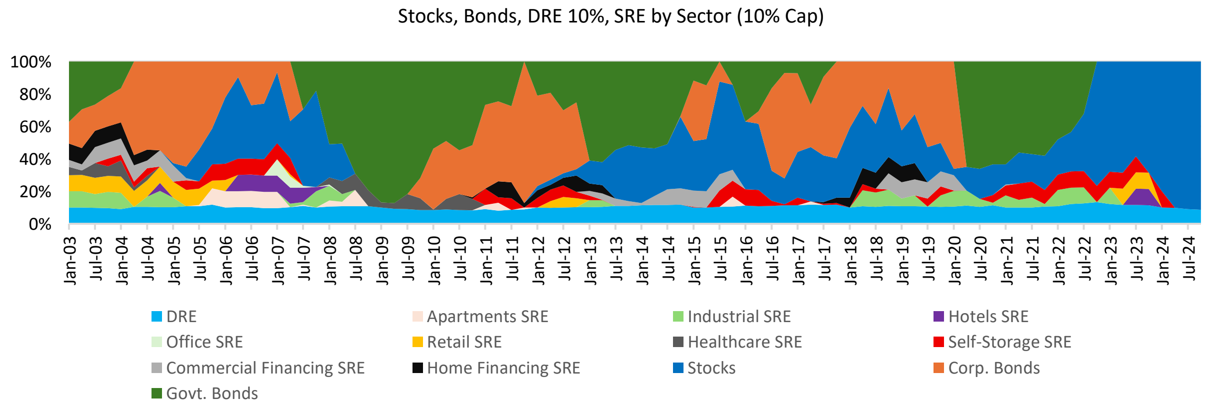
Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Appendix 9: Portfolio Compositions over Time for the Maximum Sharpe Ratio Strategy, 2003-2024





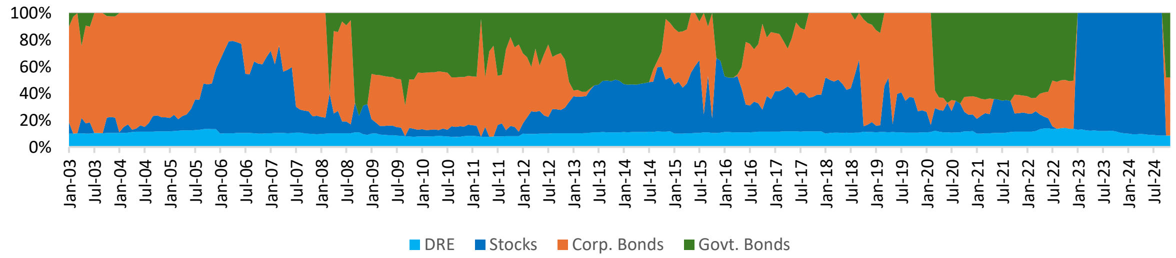




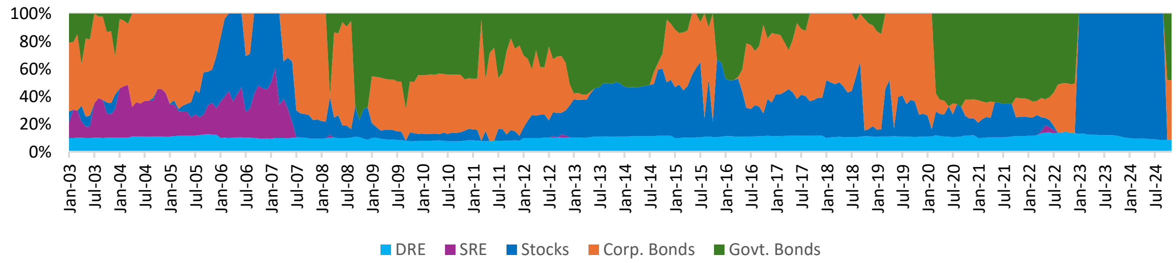
Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Appendix 10: Portfolio Compositions over Time with VIX-Based Regime-Switching, 2003-2024

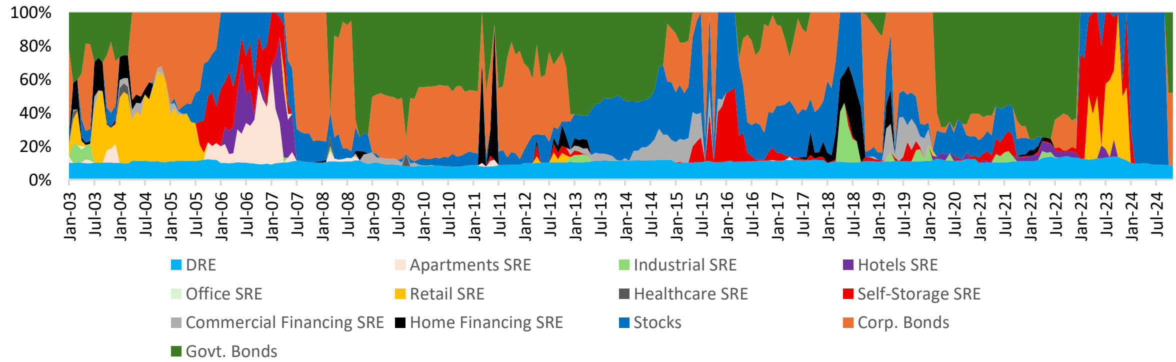
Stocks, Bonds, DRE 10%



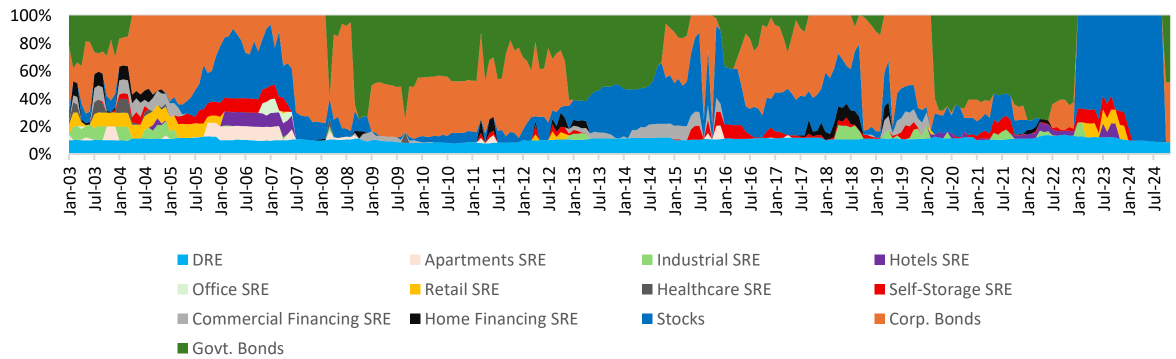
Stocks, Bonds, DRE 10%, SRE Aggregate



Stocks, Bonds, DRE 10%, SRE by Sector (No Cap)

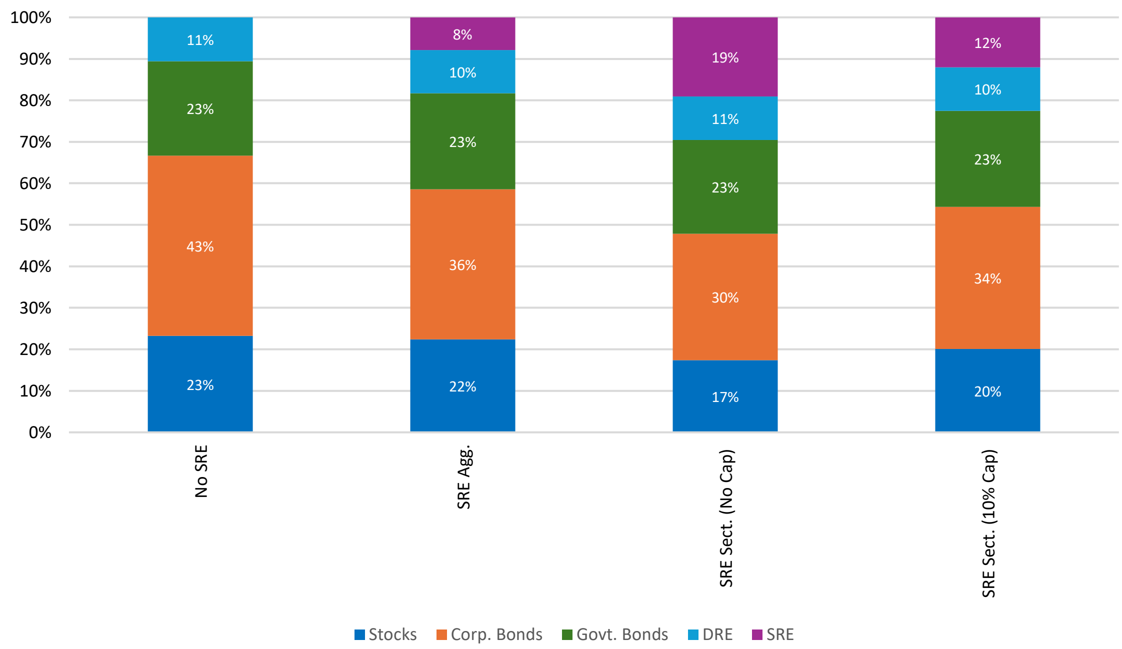


Stocks, Bonds, DRE 10%, SRE by Sector (10% Cap)



Sources: NAREIT, Bloomberg, FRED, and authors' calculations.

Appendix 11: Average Mixed-Asset Portfolio Allocations for the GDP-Based Regime-Switching Strategy with Stocks Capped at 50%, 2003-2024



Sources: NAREIT, Bloomberg, FRED, and authors' calculations.