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TAIL RISK DIVERSIFICATION STRATEGY WITH FLIGHT-FROM-LOSS APPROACH: EVIDENCE FROM U.S. REITs

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Abstract. This study introduces a novel portfolio allocation strategy, the flight-from-loss approach, designed to diversify tail risk in the REIT market. The strategy reallocates capital toward assets that have historically outperformed during periods of extreme REIT losses, aiming to reduce downside risk and improve portfolio efficiency. Using U.S. REIT data from 1993 to 2023, we demonstrate that our portfolio approach reduces tail risk significantly, while also enhancing Sharpe ratios compared to a REIT-only benchmark portfolio. These diversification benefits are particularly significant during market crises, such as the subprime mortgage crisis, when risk reduction exceeds 30%. Our analysis further reveals that the minimum-variance and tangency portfolio approaches consistently outperform the equal-weight method in both risk control and performance efficiency. To test the strategy's generalizability, we applied it to the Fama-French 30 industry portfolios, where the results of some industries indicate even stronger risk reduction and Sharpe ratio gains than in the REIT market. These findings suggest that the flight-from-loss strategy offers a practical, cross-sector solution for managing concentrated portfolio risks.

Keywords: diversification, tail risk, portfolio allocation, Real Estate Investment Trusts (REITs), risk management.

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1. Introduction

Since the global financial crisis, the study of tail risk and its interdependence across financial assets has become increasingly important for both researchers and portfolio managers (Boyson et al., 2010; Christoffersen et al., 2012). Effective risk management and portfolio allocation rely heavily on understanding how tail risk behaves across equities and different asset classes, as the benefits of diversification largely depend on the degree of market connectedness. While previous studies have primarily focused on diversification through time-varying correlation structures across multiple asset classes, limited attention has been given to strategies for directly mitigating extreme losses in a specific target asset. This gap is critical, as investors often hold underdiversified portfolios, exposing them to significant tail risk (Merton, 1987). Such portfolios remain vulnerable to severe financial shocks, as demonstrated by empirical findings that link underdiversification with higher exposure to adverse events (Xu & Malkiel, 2003). Therefore, developing strategies to control extreme downside risk within a particular asset or sector is essential, especially for investors with concentrated portfolios or when the target asset plays a pivotal role in overall wealth preservation.

This paper addresses this gap by proposing a novel portfolio allocation framework called the "flight-from-loss" strategy. This approach aims to manage tail risk by reallocating capital away from a target asset to other assets that have historically shown stronger defensive performance, particularly during periods of extreme losses for the target asset. The strategy draws inspiration from the well-established "flight-to-quality" phenomenon, where bonds often serve as a safe haven during market turbulence. The flight-from-loss method extends this concept by identifying assets that have demonstrated resilience relative to the target asset in past market stress events. By systematically reallocating exposure to such assets, the strategy offers a practical tool for investors seeking to reduce the vulnerability of their concentrated holdings to extreme market downturns.

We utilize publicly listed U.S. equity Real Estate Investment Trusts (REITs) as the target asset to investigate tail risk diversification due to their unique market characteristics and structural importance in global portfolios. REITs are firms that manage income-producing real estate assets, such as properties and mortgages, and offer returns to shareholders through dividends and capital gains. Several critical factors make the U.S. REIT market particularly suitable for studying tail risk management strategies. First, REITs have emerged as a significant alternative investment vehicle over recent decades, with a global market capitalization of $1.984 trillion as of 2023Q4.[1] The REIT structure, designed to promote transparency and liquidity in real estate markets, has been increasingly adopted in both developed and developing countries. Given that the global commercial real estate market is valued at approximately $32.4 trillion, the REIT market still holds substantial growth potential, further highlighting its systemic importance in investment portfolios. Moreover, the "five or fewer" rule, which prevents five or fewer shareholders from controlling more than 50% of a REIT's shares, encourages broader ownership dispersion (Capozza & Seguin, 2003). This regulation implies that understanding tail risk management in the REIT market can offer practical investment implications for both institutional and individual investors.

Second, the U.S. REIT market is the largest and most mature globally, accounting for approximately 67% of the total global REIT market with a market capitalization of $1.35 trillion as of 2023Q4. Understanding tail risk diversification in such a dominant market provides valuable insights for both domestic and international investors. Third, REITs are inherently vulnerable to extreme downside risks, making them a compelling subject for tail risk analysis. During the global financial crisis, REIT stocks exhibited significantly higher volatility compared to other equity sectors, even though the prices of underlying income-producing properties remained relatively stable (Sun et al., 2015). This volatility can be attributed to structural factors unique to REITs, such as mandatory high dividend payouts, limited cash holdings, and highly leveraged capital structures, which increase susceptibility to liquidity crises and fire sales during downturns (Hardin et al., 2009; Kawaguchi et al., 2017). Therefore, developing tailored portfolio strategies for managing REIT-specific tail risk exposure is crucial. Proper risk management tools can empower investors to better safeguard their portfolios against extreme downside events while maintaining exposure to the benefits of income-generating real estate assets.

Using aggregate U.S. REIT returns from 1993 to 2023, this study investigates whether REIT tail risk can be mitigated by reallocating capital to assets that historically performed well during extreme REIT losses. Our methodology involves three steps: (1) identifying a set of high-performing assets during left-tail REIT events by ranking historical returns from an asset pool, (2) estimating portfolio weights for the selected assets using three allocation methods – minimum-variance (focused on risk minimization), tangency portfolio (maximizing the Sharpe ratio), and naive equal-weight (allocating equally across selected assets), and (3) constructing a final portfolio by combining the returns from the weighted selected assets with varying allocations to REITs. We then assess the portfolio's performance by comparing its out-of-sample results against a REIT-only benchmark, focusing on reductions in tail risk and improvements in portfolio efficiency, such as Sharpe ratio growth.

Among the various asset classes available for diversification, we focus on two primary types: industry-level equities and safe-haven assets. Industry-level equities serve as our baseline diversification tool, as most investors are widely exposed to public equities across multiple sectors. To further strengthen the risk management potential, we incorporate safe assets, such as government bonds, gold, and stable currencies, which have historically demonstrated defensive qualities during periods of market stress. These safe assets help address systematic risk factors that may simultaneously impact both REITs and industry-level equities. Based on these two asset groups, we design and compare two portfolio strategies: (1) Industry 100%, which relies solely on industry-level equities for diversification, and (2) Industry 50% & Safe asset 50%, which balances industry equities and safe assets equally. We combine these strategies with a fixed rate of investment in REITs.

Our allocation strategy demonstrates substantial out-of-sample diversification benefits, effectively reducing risk and improving portfolio efficiency. When maintaining a fixed 50% allocation to REITs, the Industry 100% strategy reduces tail risk by over 20% using the minimum-variance weighting, while the tangency portfolio improves the Sharpe ratio by more than 20%. Even greater diversification advantages arise when incorporating safe assets alongside industry equities. Under the Industry 50% & Safe asset 50% strategy, tail risk is reduced by over 30% across all weighting schemes, with significant additional Sharpe ratio improvements, particularly for the minimum-variance and equal-weight portfolios. In addition, applying the strategy to the Fama-French 30 industry portfolios confirms significant risk reduction and Sharpe ratio gains across most sectors, often surpassing the results observed in the REIT market. This consistency across multiple asset classes suggests that the flight-from-loss strategy offers a reliable and broadly applicable framework for managing tail risk in various investment contexts.

Our study contributes to the portfolio-diversification literature, with a particular emphasis on managing tail risk. Since Markowitz's (1952) mean–variance frontier, most diversification work has centred on cross-border, cross-asset, and cross-industry allocations (Ferson & Harvey, 1993; Bekaert & Urias, 1996; Ang & Bekaert, 2002), yet the variance metric assumes thin tails. Responding to this limitation, portfolio theory has progressively shifted toward explicit control of fat-tailed losses. Early extensions substituted variance with downside measures such as Value-at-Risk and expected shortfall (Campbell et al., 2001; Christoffersen et al., 2012). While extensions of this framework have aimed to account for tail risk, their out-of-sample performance has been mixed, fuelling interest in robust alternatives such as equal-weight portfolios (DeMiguel et al., 2009), but the growing evidence on fat-tailed risk underscores the need for allocation rules that directly target extreme downside exposure.

[1] Refert to EPRA Global Real Estate Total Markets Table 2023 Q4

Recent literature has advanced the understanding of tail risk management. Sanford (2022) minimises an option-implied expected shortfall derived from Ross's Recovery Theorem and documents materially smaller drawdowns than both historical-ES and equal-weight strategies, while Gava et al. (2021) blend extreme-value theory with risk-parity to curb negative skewness without sacrificing long-run returns. Complementing the options approach, Almeida et al. (2024) construct a high-frequency daily tail-risk premium–the gap between risk-neutral and physical expected shortfall–showing it predicts next-day equity and variance premia as well as characteristic-sorted portfolio returns, thereby confirming that markets dynamically price anticipated crashes.

These insights resonate with the literature on risk spill-overs, where diversification benefits erode once extreme events propagate through connected markets. COVID-19, for example, intensified tail-risk networks across nineteen equity markets and elevated cross-asset contagion among a variety of asset classes (Guo et al., 2021; He & Zhang, 2024). Research on listed real estate remains sparse. Prior research on REITs has primarily examined risk transmission among international REITs or between REITs and broader asset classes (e.g., Liow et al., 2009; Zhou, 2012; Hoesli & Reka, 2013; Chiang et al., 2017). The few available studies show that sector-specific tail exposure helps explain U.S. REIT returns (Song & Liow, 2023) and that techniques such as volatility-targeting or jump-enhanced VaR can temper REIT drawdowns (Odusami, 2021). Yet none of this work identifies which companion assets consistently serve as safe havens when REIT portfolios experience their deepest losses.

Our study fills this gap by extending the classical "flight-to-quality" intuition into a flight-from-loss framework that screens assets according to their realised performance in past REIT tail events and reallocates capital dynamically. By integrating robust, tail-aware optimisation with an understanding of extreme downside risk, we deliver a multi-asset allocation rule that reduces out-of-sample expected shortfall significantly. In doing so, we provide a targeted, practical tool for investors seeking to manage concentrated tail risk in REIT-dominated portfolios while contributing fresh evidence to the broader literature on safe-haven asset selection and dynamic risk management.

The rest of the article is organized as follows. Section 2 explains the research methodologies for the portfolio strategy of flight-from-loss and the estimation of portfolio gain measures. Section 3 shows the summary of data. Section 4 presents the results of out-of-sample portfolio analysis. Section 5 provides various robustness checks. Section 6 concludes this article.

2. Research methodology

2.1. Flight-from-loss strategy

We employ a portfolio allocation strategy designed to diversify the time-varying tail risk of REITs by building on the well-known flight-to-safety concept in finance. The flight-from-loss strategy is motivated by the well-established theory of flight to safety, a phenomenon whereby investors reallocate capital from riskier to safer assets during periods of heightened uncertainty. Classic models attribute this behavior to increased risk aversion under uncertainty (Caballero & Krishnamurthy, 2008; Brunnermeier & Pedersen, 2009), where investors seek quality, liquidity, or macroeconomic resilience. Extending this intuition, our strategy reallocates REIT holdings toward equity sectors historically resilient during REIT-specific stress, effectively creating a diversified hedge within the risky asset space.

Our strategy enhances portfolio resilience by integrating REITs with equity sectors that exhibit complementary performance during REIT-specific downturns. For instance, while REITs are exposed to physical damage and financing risk during natural disasters or credit stress, consumer staples (e.g., food and beverage producers) tend to sustain demand due to their essential nature and low income elasticity. Smoke industries similarly provide defensive characteristics, as demand remains inelastic even during economic stress, reflecting habitual consumption patterns. Utilities, protected by regulatory frameworks and predictable cash flows, offer further defensive stability. These industries could act as partial hedges, not because they are risk-free, but because their cash flow dynamics and demand profiles differ fundamentally from real estate. By embedding these sectors ex ante, the strategy provides structural protection that smooths portfolio performance in contingent downside scenarios. This mirrors the within-equity portfolio reallocation that global investors undertake in response to climate disasters, as documented by Ferriani et al. (2024), suggesting that selective industry exposure can function as an internal flight mechanism even without rotating into traditional safe-haven assets.

We emphasize two key features of our approach. First, we go beyond aggregate safe assets and identify specific equity industries that historically act as dynamic complements to REITs during turbulent periods (e.g., utilities, consumer staples), thereby improving resilience through selective diversification. Second, we propose a systematic allocation rule that does not rely on market timing but prepares in advance by maintaining a balanced exposure to both industry and safe assets based on historical downside relationships, thus mitigating the need for precise crisis prediction. Although our approach may not capture turning points in real time, it could be particularly valuable for retail investors–one of the major REIT investor groups–who often face practical challenges in reallocating portfolios swiftly during market downturns. Together, these features aim to operationalize the "flight-from-loss" concept as a robust, implementable strategy, even under conditions of limited predictability.

Our allocation approach involves three systematic steps. First, we identify a set of assets with historically strong returns during severe REIT losses, focusing on those that have provided a defensive cushion in the past. For instance, if REITs experienced a sharp decline in a particular period, we could select assets like consumer staples or healthcare equities if those sectors remain relatively stable during the same period. Second, we estimate portfolio weights for the identified assets using three allocation methods: (1) the minimum-variance approach, (2) the tangency portfolio, and (3) a naive equal-weight allocation. Third, we construct a diversified portfolio by combining the selected assets and REITs, allocating 50% of the investment to each.[2]

For asset selection, we consider two core strategies: Industry 100% and Industry 50% & Safe asset 50%. The Industry 100% strategy relies solely on industry-level equities to diversify REIT risk, while the Industry 50% & Safe asset 50% strategy allocates capital equally between industry assets and traditionally defensive safe-haven assets, such as U.S. Treasury bonds or gold. Additionally, we implement a quarterly rebalancing approach to manage turnover and transaction costs, minimizing excessive adjustments compared to monthly or more frequent rebalancing.[3]

Finally, the performance of our strategies is assessed against a REIT-only benchmark, using key metrics such as the risk reduction rate and Sharpe ratio improvement. These measures help evaluate whether our diversified portfolios achieve both lower downside risk and better risk-adjusted returns compared to a concentrated REIT investment. This structured approach not only provides a practical tool for REIT investors but also offers broader insights into managing concentrated portfolio risks using historical market behavior.

Industry 100% strategy

We begin with the Industry 100% strategy using only industry-level equity returns to diversify REIT risk. We apply the Fama-French 30 industry classification to ensure a comprehensive representation of industry sectors in the U.S. equity market.[4]

The first step involves identifying industries that have shown stronger historical returns during periods of extreme REIT losses. Specifically, for each rolling window, we measure industry returns on days when the REIT market experiences severe declines, defined as returns below a chosen value-at-risk (VaR) threshold. The expected return for each industry conditional on REIT losses is calculated as:

$$R = E\left[r_i \mid r_{REIT} < VaR_{REIT}^{\alpha}\right] = \left(\bar{r}_1, \bar{r}_2, \bar{r}_3, \ldots, \bar{r}_{K-1}, \bar{r}_K\right)', \quad (1)$$

where R is a vector of average returns $(\bar{r}_1, \bar{r}_2, \ldots, \bar{r}_K)$ for all industries, conditional on the extreme risk of REIT lower than the value at risk of a α probability level. We then rank the industries based on their average returns calculated in Step 1. The industries with the highest returns during REIT stress periods are selected for the portfolio. Specifically, we choose the top N industries with the strongest historical performance using the ranking function:

$$R_{IND}^{Selected} = \{\left(\bar{r}_1, \bar{r}_2, \bar{r}_3, \ldots, \bar{r}_{K-1}, \bar{r}_K\right) \mid rank\left(R\right) \le N\} = \left(r^1, r^2, \ldots r^N\right)', \quad (2)$$

where $N \in$ Ordinal number, $N \le K$, $rank(\cdot)$ indicates the rank function that sorts industries in descending order of returns, ensuring those with the highest defensive performance are chosen. The set of selected industries is then represented as:

$$Selected\ Industry = \left\{IND^1, IND^2, \ldots, IND^N\right\}, \quad (3)$$

where IND^N indicates N-th high-performance industry during extreme REIT losses. The selected industries will form the basis of the Industry 100% diversified portfolio. We use Fama-French 30 industry returns and select the top five industries (N = 5).[5]

In the second step, we calculate portfolio weights for the selected industries using three well-established asset allocation methods: minimum-variance, tangency portfolio, and naive equal-weight approaches. These methods aim to optimize the balance between risk and return based on the historical performance features of the selected industries.

First, the minimum-variance approach focuses on minimizing overall portfolio risk by reducing return volatility. This method calculates the portfolio weights that achieve the lowest possible variance given historical return data. Although a minimum-variance portfolio sacrifices portfolio returns to achieve low risk, previous literature has shown that using only covariance of portfolio returns for allocation could be sufficient to identify optimal weights (Green & Hollifield, 1992; Jagannathan & Ma, 2003).

This is comparable to constructing a financial portfolio that balances assets with different risk profiles so that

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[2] The fixed 50% allocation to REITs is intended to keep the analysis focused on the diversification benefits of the selected assets, rather than on the standalone risk-return profile of REITs. Without this constraint, the optimization process might excessively reduce REIT exposure when their risk-return characteristics are less attractive, confounding the evaluation of diversification effects. By holding REIT allocation constant, we ensure that performance differences reflect the contribution of the complementary assets, not just reduced REIT risk. We also examine the diversification effects under varying REIT allocations in a later section.

[3] The fixed 50:50 allocation between industry and safe assets is designed to prevent the low-risk nature of safe assets from overwhelming the portfolio. Without this cap, the ranking process would heavily overweight safe assets–especially during market stress–crowding out industry exposure and masking the diversification effects we aim to study. This split ensures meaningful equity exposure, allowing us to assess each asset's marginal contribution to tail-risk mitigation while preserving a balanced trade-off between stability and risk sharing.

[4] There is a trade-off in opting industry classification. If we choose too specified industry classification, several industries could be subject to common systematic factors due to similar industrial business cycle. If we choose too roughly constructed industry classification, we may not find proper industries that work better against losses of the REIT market. Thus, we choose Fama-French 30 industry classification since this sorting well balance this tradeoff. In our unreported results, we find that our results are qualitatively similar and robust to other classicificaitons, such as Fama-French 17 and 48 industries.

[5] The number of selected industry could be arbitrary. Thus, we conduct robustness check with different numbers in the later section.

losses in one part are offset by gains or stability in another, keeping overall fluctuations in check. Rather than concentrating solely on the highest-returning investments, the minimum-variance approach focuses on how assets interact with one another, seeking combinations that dampen overall volatility–much like diversifying a business across multiple revenue streams, where the strength of one line can cushion the impact of downturns in another, ultimately stabilizing total earnings over time.

The optimization problem is formulated as:

$$\min_{W} \sigma^2_{p,W} \;\; s.t. W' \times \mathbb{I}_N = 1,\; w_i \geq 0\left(i = 1,\ldots,N\right), \tag{4}$$

where $\sigma^2_{p,W}$ is $W' \times \Omega \times W$ a variance of portfolio returns based on W, which is a weight vector of N industries. Ω is a covariance matrix, $\mathbb{I}_N$ is a vector of N ones. Across all weighting methods, we restrict portfolios to long-only positions to better align with practical investment constraints faced by retail investors. This optimization approach essentially finds the smoothest combination of weights that keeps the portfolio as steady as possible, like adjusting the balance of multiple moving parts so that when one fluctuates, the others help absorb the shock. Then, the optimal weights for the minimum-variance portfolio are derived using:

$$W^{IND}_{MV} = \frac{\Omega^{-1} \times \mathbb{I}_N}{\mathbb{I}_N{}' \times \Omega^{-1} \times \mathbb{I}_N}, \tag{5}$$

where W^{IND}_{MV} is the optimal weight for the selected N industries based on the minimum-variance approach. This allocation approach emphasizes risk reduction by prioritizing industries with lower historical return volatility and minimal correlation with each other.

Second, the tangency portfolio (or maximum Sharpe ratio portfolio) seeks to optimize the balance between risk and return by maximizing the Sharpe ratio. Unlike the minimum-variance approach, which focuses solely on reducing risk without regard for returns, the tangency portfolio explicitly considers both expected returns and risk, aiming for the most efficient trade-off between the two. For example, it avoids overweighting extremely low-risk assets that may drag down returns, ensuring the portfolio achieves the highest possible return for each unit of risk taken. It identifies the portfolio that offers the highest return per unit of risk, incorporating the risk-free rate (r_f):

$$\max_{W} \frac{W' \times \mu - r_f}{\left(W' \times \Omega^{-1} \times W\right)^{\frac{1}{2}}} \text{ s.t. } W' \times \mathbb{I}_N = 1,\; w_i \geq 0\left(i = 1,\ldots,N\right). \tag{6}$$

As consistent with the minimum variance method, we require a short-sale constraint on this problem. After solving the problem, we can derive the optimal weight of the tangency portfolio:

$$W^{IND}_{TG} = \frac{\Omega^{-1} \times \left(\mu - r_f\right)}{\mathbb{I}_N{}' \times \Omega^{-1} \times \mathbb{I}_N}, \tag{7}$$

where $\mathbb{I}_N$ is a vector of N ones, Ω is a covariance matrix. W^{IND}_{TG} indicates a weight vector that maximizes the Sharpe ratio among all portfolios composed of N industries. This tangency portfolio offers an efficient solution for achieving the best possible balance between risk and return, taking both dimensions into account.

Finally, the naive equal-weight approach allocates capital equally across all selected industries, with each industry receiving a weight of $1/N$ (Liu, 2016). Despite its simplicity, previous studies have shown that equal-weighted portfolios can perform competitively against more complex allocation models, often providing strong diversification with lower estimation errors (e.g., DeMiguel et al., 2009).

In the final step, we construct out-of-sample portfolio returns using the portfolio weights estimated from the three allocation strategies described earlier: minimum-variance, tangency portfolio, and naive equal-weight. This step evaluates the effectiveness of the portfolio strategies in reducing risk and enhancing performance beyond the sample period used for portfolio construction.

We first calculate the out-of-sample portfolio return using the selected industry assets and their assigned weights. The return for the industry-only portfolio is computed as:

$$r^{IND}_{P,t+1} = W_t{}' \times R^{IND}_{t+1}, \tag{8}$$

where R^{IND}_{t+1} is the return vector for the selected industries in t+1. $W_t{}'$ represents the portfolio weights assigned to the selected industries at time t. The portfolio weights are determined using one of the three allocation strategies: minimum-variance, tangency portfolio, or naive equal-weight. These weights are fixed for the next period and adjusted quarterly to reduce excessive turnover and transaction costs. $r^{IND}_{P,t+1}$ is out-of-sample returns of the industry portfolio for time t+1.

Then, we construct a diversified portfolio by combining REIT returns with the selected industry portfolio returns ($r^{IND}_{P,t+1}$). To maintain consistency and avoid the influence of REIT's risk-return characteristics disproportionately driving the results, we apply a fixed allocation of 50% to REITs and 50% to the selected industries. This ensures that the diversification benefits are driven by the selection of complementary assets rather than reduced REIT exposure. he return for the combined portfolio is calculated as:

$$r^{REIT+IND}_{P,t+1} = \beta \times r^{REIT}_{t+1} + \left(1 - \beta\right) \times r^{IND}_{P,t+1}, \tag{9}$$

where r^{REIT}_{t+1} and $r^{IND}_{P,t+1}$ are the return on the REIT and industry portfolios, respectively, at time t+1. β represents the fixed allocation ratio for REIT investment, set at 50%. $r^{REIT+IND}_{P,t+1}$ is the final out-of-sample portfolio returns composed of REIT and selected industries. We adopt 50% for β in the assumption that REIT investors hold a significant percentage of assets in REIT.

Industry 50% & Safe asset 50% strategy

There is a possibility that aggregate industry-level and REIT returns could have common systematic factors because both composite returns are based on the stock market. If this is the case, our portfolio strategy might be less effective for controlling extreme risk during market downturn periods when systematic risk dominates industry-specific risk. To address this possibility, we further consider traditional safe assets that have shown defensive effects during uncertain periods. Among many others, we choose six popular safe assets: U.S. 10-year government bond, UK pound (GBP), and Japanese yen (JPY), Swiss franc (CHF), gold, and platinum.

The Industry 50% & Safe asset 50% strategy follows a similar methodology to the Industry 100% approach but expands the asset pool by incorporating both industry-level equities and traditionally defensive safe assets to diversify REIT risk further. In the allocation strategy, however, we do not combine safe assets with industry-level equities in the same rank function since the underlying roles and risk-return features of the two asset types are significantly different. We instead separately apply the same rank methodology to select safe assets with higher performance.

We begin by selecting safe assets based on their historical performance during extreme REIT downturns. Similar to the industry selection process, safe assets are ranked according to their average returns on days when REIT losses exceed a predefined Value-at-Risk (VaR) threshold. From this ranking, the top-performing safe assets are selected to complement the industry portfolio. For our analysis, we focus on the top three safe assets from a pool of six candidates.

The portfolio weights of selected safe assets are then calculated using the same three allocation strategies employed in the Industry 100% strategy. A key distinction in this strategy is the fixed allocation constraint, with 50% allocated to industry assets and 50% to safe assets. This balanced split prevents the lower volatility of safe assets from dominating the portfolio, ensuring both asset groups contribute meaningfully to risk reduction and performance improvement.

Finally, the combined portfolio return is calculated by blending REIT returns with the diversified industry and safe asset portfolio:

$$r_{P,t+1}^{REIT+IND+SA} = \beta \times r_{t+1}^{REIT} + \left(1-\beta\right) \times r_{P,t+1}^{IND+SA}, \tag{10}$$

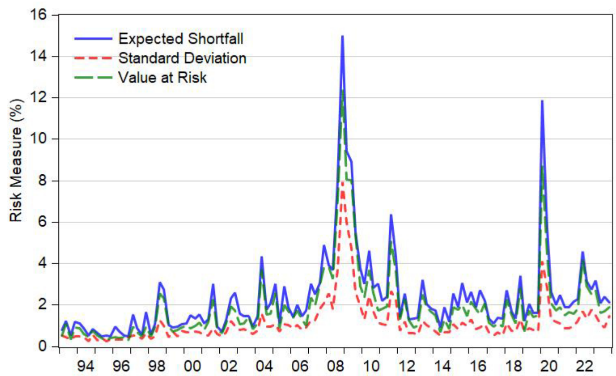
where $r_{P,t+1}^{IND+SA}$ is the out-of-sample portfolio return based on selected industry and safe assets. We maintain 50% for β for consistency across strategies. $r_{P,t+1}^{REIT+IND+SA}$ represents the final out-of-sample portfolio return vector composed of REIT, selected industries, and safe assets.

2.2. Out-of-sample diversification benefit

To assess whether our portfolio strategy delivers superior performance compared to a REIT-only benchmark, we evaluate out-of-sample diversification benefits by comparing portfolio returns when REIT investors apply our strategy versus holding only REITs. The goal is to determine if our approach effectively reduces downside risk and enhances overall portfolio efficiency.

To measure diversification effectiveness, we use widely recognized risk and performance indicators. First, we use volatility, estimated as the standard deviation of daily portfolio returns during quarter $t+1$. Then, for our main performance measures, we use two popular tail risk measures: value-at-risk (VaR) and expected shortfall (ES). VaR is estimated as the maximum expected portfolio loss at a specified confidence level (5% in our study) based on historical data. VaR estimates the threshold return below which the portfolio is unlikely to fall under normal market conditions. ES, also known as conditional VaR, is estimated as the average return loss when portfolio returns fall below the VaR threshold, focusing on extreme downside risk. Mathematically, ES is calculated as $\mathrm{ES}_{t+1}^{\alpha} = -\mathrm{E}[r_{d,t+1} \mid r_{d,t+1} \le \mathrm{VaR}_{t+1}^{\alpha}]$, where $r_{d,t}$ is the daily return for the REIT market at quarter $t+1$, $\mathrm{ES}_{t+1}^{\alpha}$ and $\mathrm{VaR}_{t+1}^{\alpha}$ are the expected shortfall and value-at-risk at quarter $t+1$. We choose 5% as a threshold probability α following the rule suggested by Gabaix et al. (2006).[6]

Figure 1 shows the evolution of three risk measures of the REIT market over the sample period. As shown, the tail risk of the U.S. REIT market has countercyclical patterns with significant spikes during the global financial crisis, European debt crisis, and recent COVID-19 crisis. Increases in risk over other periods are relatively weaker than these periods. This suggests that the performance of our investment strategy will be particularly important during periods of turmoil.



Note: This figure plots the quarterly risk measures of the value-weighted U.S. REIT market over the period 1993 to 2023. We report the time-series evolution of expected shortfall, value-at-risk (5% threshold), and volatility (standard deviation), estimated from daily returns within each quarter.

Figure 1. Time-series of risk in the REIT market

We then estimate two portfolio gain measures: risk reduction rate and improvement of portfolio efficiency based on the Sharpe ratio. Firstly, we estimate the effects of risk reduction when combined with the selected assets that had shown higher performance in the past periods of extreme loss of REITs. Specifically, the risk reduction rate can be represented as follows:

$$RD = 1 - \frac{Risk_{t+1}^{*}}{Risk_{t+1}^{REIT}}, \tag{11}$$

where $Risk_{t+1}^{REIT}$ is a benchmark risk (volatility, value-at-risk, and expected return) based on the daily return of the

[6] Gabaix et al. (2006) suggest the threshold probability of 5% for the unconditional estimation. This rule is also employed by Kelly and Jiang (2014) who investigate asset pricing features of tail risk.

REIT-only portfolio at quarter t+1, $Risk^{*}_{t+1}$ is a risk of the diversified portfolio based on the industry only or industry & safe asset strategies. *RD* indicates a proportion of risk reduction if we use our portfolio strategies compared with a REIT-only investment.

Second, we investigate whether our diversified portfolios provide efficiency in terms of both risk and return. As tail risk can be regarded as risk under the Sharpe ratio approach, we can construct the Sharpe ratio gain:

$$SG = \frac{Sharpe^{*}}{Sharpe^{REIT}} - 1, \tag{12}$$

where $Sharpe^{*} = \frac{W_t^{*'} \times \mu_{t+1} - r_f}{Risk^{*}_{t+1}}$, and $Sharpe^{REIT} = \frac{W_t^{REIT'} \times \mu_{t+1} - r_f}{Risk^{REIT}_{t+1}}$. *SG* denotes an improvement rate in portfolio efficiency when we use our portfolio strategy. We estimate the above two portfolio gain metrics for volatility, VaR, and ES, respectively.[7] Specifically, for every rolling window estimation, we obtain the quarterly distribution of out-of-sample Share ratio improvement and risk reduction, and then estimate the average values for the full sample period.

3. Data

We obtain daily returns of publicly listed U.S. equity REITs between 1993 and 2023 from the Center for Research in Security Prices (CRSP). Our sample period is the modern REIT era, which covers the introduction of UPREIT legislation, the subprime crisis, the COVID-19 pandemic, and the recent high-interest rate environment. We compare the REIT sample with the equity REIT list of Feng et al. (2011) and the historical list of U.S. equity REIT constituents for the FTSE NAREIT U.S. Real Estate Index from the National Association of Real Estate Investment Trusts (NAREIT). To reduce survivorship bias, we include delisted REITs during the sample period. Based on the daily returns of individual REITs, we construct a daily value-weighted return, which represents the aggregate REIT return in our study. In the same period, we collect value-weighted daily returns of Fama-French 30 industries and a 1-month risk-free rate from the data library of Kenneth French.[8]

For safe assets, we obtain daily total return indices for the U.S. 10-year government bond, the UK pound (GBP), the Japanese yen (JPY), the Swiss franc (CHF), gold, and platinum from Datastream.[9] We convert them into daily re-

[7] RD_{vol}, RD_{VaR}, and RD_{ES} (SG_{vol}, SG_{VaR}, and SG_{ES}) are risk reduction (Sharpe ratio growth) for volatility, VaR, and ES, respectively.

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[9] Japanese yen's safe-haven role has become less consistent in recent years, particularly after 2020, possibly due to shifting global risk dynamics, monetary policy changes, and evolving investor preferences (Li et al., 2024; Chen & Mo, 2025). Nonetheless, we include the yen in our analysis because of its historically well-established reputation as a global safe asset, especially during past periods of financial turbulence, which remains relevant for understanding dynamic patterns of cross-asset relationships.

Table 1. Summary statistics

	Mean	St. Dev.	p25	Median	p75
Panel A. REIT					
REIT	0.07	1.54	–0.43	0.08	0.60
Panel B. Fama-French 30 Industries					
food	0.04	0.98	–0.44	0.06	0.55
beer	0.05	1.17	–0.53	0.05	0.61
smoke	0.05	1.53	–0.65	0.06	0.78
games	0.05	1.72	–0.74	0.06	0.88
books	0.03	1.42	–0.61	0.05	0.70
hshld	0.04	1.09	–0.48	0.05	0.57
clths	0.05	1.52	–0.70	0.06	0.82
hlth	0.05	1.15	–0.52	0.07	0.66
chems	0.05	1.45	–0.64	0.06	0.78
txtls	0.03	1.83	–0.78	0.03	0.82
cnstr	0.05	1.57	–0.67	0.08	0.82
steel	0.05	2.07	–0.94	0.06	1.06
fabpr	0.06	1.59	–0.69	0.08	0.85
elceq	0.06	1.62	–0.75	0.06	0.88
autos	0.05	1.92	–0.82	0.06	0.96
carry	0.06	1.51	–0.65	0.08	0.80
mines	0.05	1.91	–0.97	0.03	1.07
coal	0.07	3.02	–1.38	0.03	1.50
oil	0.05	1.69	–0.74	0.05	0.89
util	0.04	1.11	–0.46	0.08	0.59
telcm	0.03	1.28	–0.55	0.05	0.65
servs	0.06	1.51	–0.62	0.10	0.80
buseq	0.07	1.76	–0.75	0.12	0.92
paper	0.04	1.21	–0.55	0.07	0.65
trans	0.05	1.38	–0.66	0.07	0.75
whlsl	0.04	1.17	–0.50	0.08	0.63
rtail	0.05	1.30	–0.60	0.08	0.70
meals	0.05	1.24	–0.58	0.07	0.69
fin	0.05	1.57	–0.59	0.07	0.72
other	0.03	1.29	–0.53	0.05	0.61
Panel C. Safe assets					
US bond	0.02	0.47	–0.25	0.02	0.30
UK pound	0.00	0.58	–0.32	0.00	0.32
Japan JPY	0.00	0.66	–0.36	0.00	0.32
Swiss franc	0.01	0.65	–0.35	–0.01	0.35
Gold	0.03	0.98	–0.42	0.01	0.49
Platinum	0.02	1.45	–0.70	0.00	0.75
Panel D. Correlation					
REIT-Industry	0.56	0.09	0.51	0.57	0.61
REIT-Safe asset	0.00	0.09	–0.06	0.01	0.06

Note: This table reports the summary statistics of daily returns for value-weighted REITs (Panel A), Fama-French 30 industry portfolios (Panel B), and six traditional safe-haven assets (Panel C) over the sample period from January 1993 to December 2023. Reported statistics include the mean, standard deviation (St.Dev), 25th percentile (p25), median, and 75th percentile (p75). Panel D presents the descriptive statistics of pairwise correlations between REIT and the Fama-French 30 industries (REIT–Industry) and between REIT and the safe assets (REIT–Safe Asset) over the sample period.

turns using the log difference of return indices. Table 1 reports summary statistics for daily returns of REIT (Panel A), Fama-French 30 industries (Panel B), and six safe assets (Panel D). Overall, average returns of safe assets are relatively smaller than REIT and the 30-industry. In Panel D of Table 1, we further present the descriptive statistics of the correlation of REIT with industry and safe asset, respectively. As shown, REIT and Fama-French 30 industries are highly and positively correlated, whereas the average correlation between REIT and safe assets is very small.

4. Empirical results

4.1. Portfolio gains from flight-from-loss

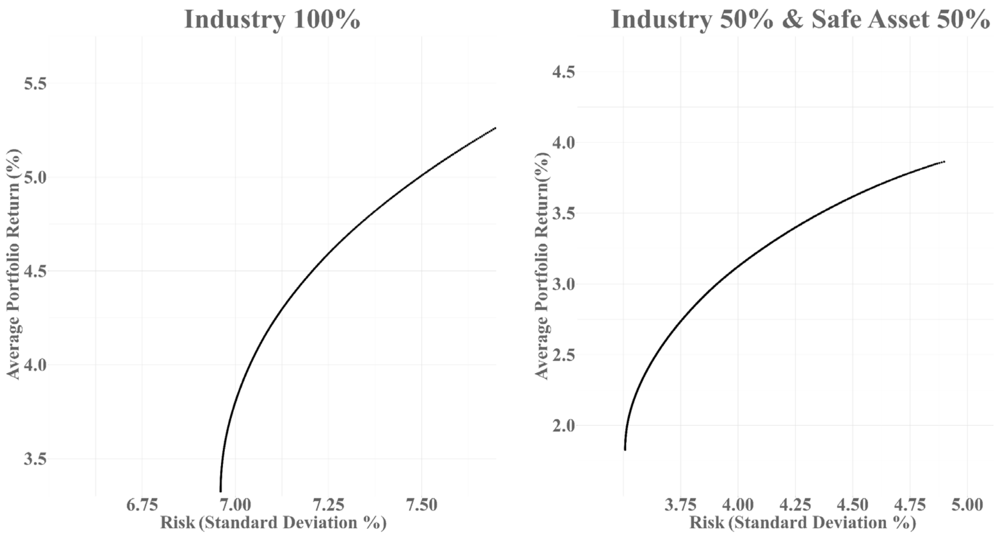
Table 2 presents the diversification benefits of the flight-from-loss strategy for REIT investors using three portfolio weighting schemes: minimum-variance (Min-var), tangency portfolio (Tangency), and equally-weighted (Equal). The results report quarterly mean returns and volatility, while Value-at-Risk (VaR) and Expected Shortfall (ES) capture the level of daily extreme loss within each quarter.

In Panel A, the Industry 100% strategy, which uses only industry-level equities, demonstrates considerable risk reduction benefits across all weighting schemes compared to a value-weighted REIT-only portfolio. The REIT-only benchmark reports a quarterly mean return of 4.116% and a volatility of 9.116%, with a VaR of 1.784% and ES of 2.435%. When using industries that historically performed better during extreme REIT losses, the minimum-variance strategy reduces tail risk the most, with VaR decreasing to 1.396% and ES to 1.895%. However, this comes with a lower mean return of 3.314%, reflecting the typical risk-return tradeoff (Liu, 2016). The tangency portfolio delivers a stronger balance of risk and return, achieving a mean return of 3.662% and a Sharpe ratio gain exceeding 10%. In contrast, the equal-weight strategy, while reducing tail risk, underperforms in terms of Sharpe ratio, suggesting it is less efficient than optimization-based methods for balancing risk and return in our context.

Table 2. Out-of-sample gains from the flight-from-loss strategy

	Undiversified	Diversified		
	REIT	Min-var	Tangency	Equal
	(1)	(2)	(3)	(4)
Panel A. Industry 100%				
Mean return	4.116	3.314	3.662	3.160
Volatility	9.116	7.002	7.172	7.204
VaR	1.784	1.396	1.429	1.452
ES	2.435	1.895	1.948	1.950
RD_{vol}		23.197	21.329	20.975
RD_{VaR}		21.756	19.856	18.580
RD_{ES}		22.178	20.006	19.923
SG_{vol}		4.840	13.097	–2.863
SG_{VaR}		2.909	11.017	–5.720
SG_{ES}		3.467	11.226	–4.138
Panel B. Industry 50% & Safe asset 50%				
Mean return		2.731	2.943	2.791
Volatility		5.621	5.754	6.106
VaR		1.105	1.141	1.221
ES		1.510	1.552	1.642
RD_{vol}		38.341	36.881	33.018
RD_{VaR}		38.044	36.016	31.518
RD_{ES}		37.979	36.278	32.576
SG_{vol}		7.586	13.282	1.209
SG_{VaR}		7.070	11.750	–1.008
SG_{ES}		6.957	12.210	0.546

Note: This table reports the performance of undiversified (REIT) and diversified portfolios with three different weight strategies, minimum variance ("Min-var"), tangency portfolio ("Tangency"), and naive equal weight ("Equal"), and the gains from the diversified portfolio. RD_{vol}, RD_{VaR}, and RD_{ES} are risk reductions for volatility, value-at-risk, and expected shortfall, respectively. SG_{vol}, SG_{VaR}, and SG_{ES} are Sharpe ratio growth for volatility, value-at-risk, and expected shortfall, respectively. Since our portfolio is rebalanced every quarter, the mean return and volatility are adjusted for the quarterly percentage (%). Value-at-risk and expected shortfall are presented as daily percentage (%) because these measures use only the extreme part of the quarterly empirical distribution. Risk reduction and Sharpe ratio growth are presented as a percentage (%). The sample period is January 1993 to December 2023.



Note: This figure provides a comparative visualization of the mean-variance efficient frontiers for two strategies: the Industry 100% allocation and the Industry 50% & Safe asset 50% allocation. Each frontier is constructed by solving portfolio optimization problems that combine REITs with either (i) a full exposure to industry assets (left panel) or (ii) a blended exposure of 50% industry and 50% safe assets (right panel). The figure reflects the average of time-varying optimal risk-return pairs across the full sample period, under a short-sale constraint. Both axes report returns and risks in percentage terms per quarter. Here, Return is defined as the expected quarterly return of the portfolio, while risk represents the standard deviation of portfolio returns (i.e., volatility) over the same period.

Figure 2. Efficient frontier

One potential problem of the industry 100% strategy is that both REIT and sectoral returns could be exposed to systematic market factors. For example, most equities are generally vulnerable to unexpected aggregate shocks. If this is the case, "flight-from-loss" might not work because there would be nowhere to fly during adverse events. Thus, we additionally add safe assets for further implementation of our strategy. Panel B investigates the Industry 50% & Safe asset 50% strategy, which combines industry assets with traditionally defensive safe assets to further mitigate risk. This strategy substantially enhances risk reduction compared to the industry-only portfolios, despite keeping a fixed 50% allocation to REITs. Tail risk reductions exceed 30% across all weighting schemes, with the minimum-variance strategy again achieving the highest reduction in both VaR (1.105%) and ES (1.510%). The tangency portfolio continues to balance risk reduction and performance effectively, while the equal-weight approach, which previously struggled, now delivers positive Sharpe ratio growth, suggesting the inclusion of safe assets plays a critical role in improving its performance.

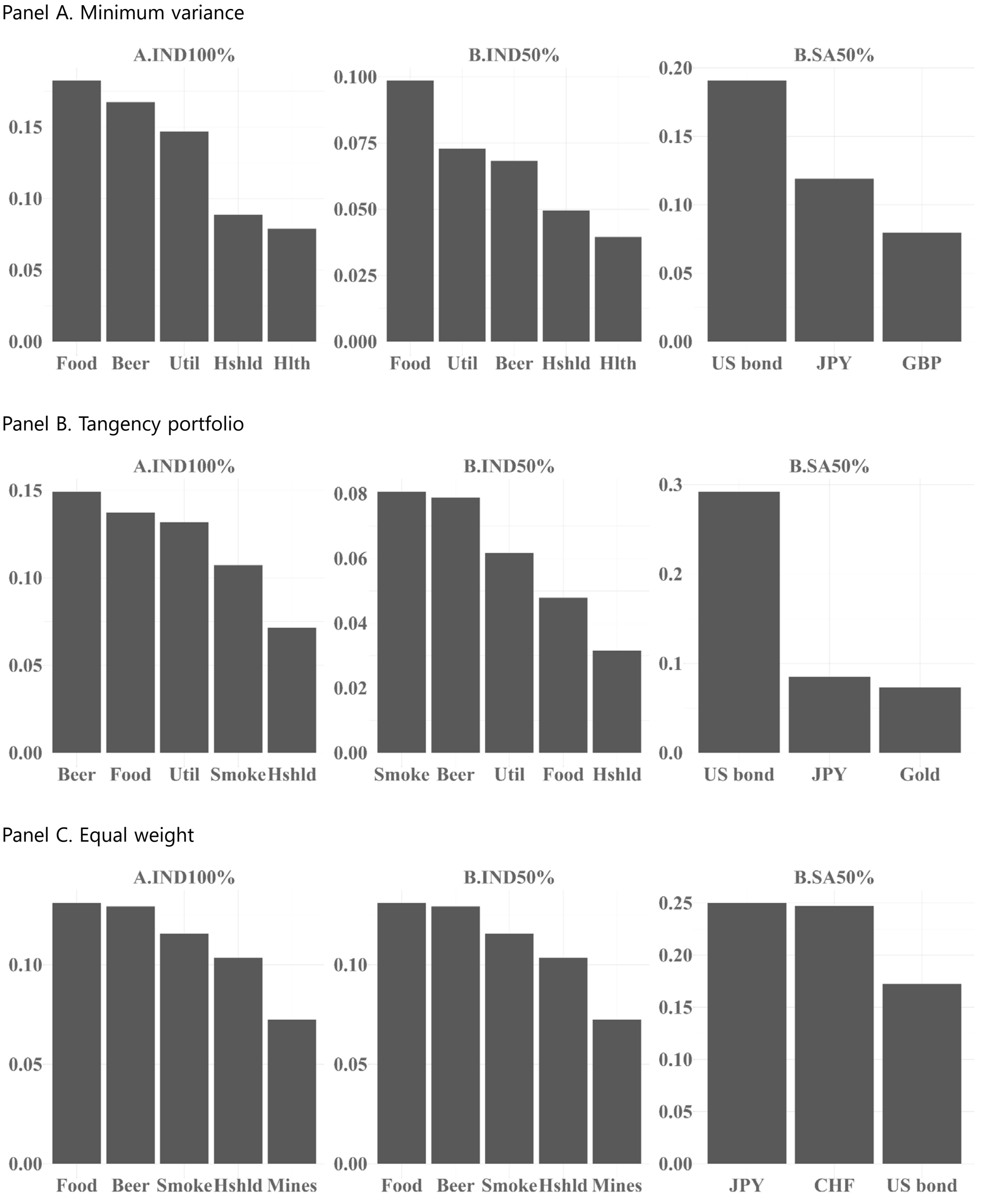
Overall, the results confirm that the minimum-variance strategy is the most effective for minimizing risk, while the tangency portfolio excels at balancing risk and return. The inclusion of safe assets further strengthens the strategy by significantly improving both risk reduction and Sharpe ratio performance, particularly for the equal-weight approach. These findings emphasize the importance of asset selection and allocation balance in achieving effective tail risk management for REIT portfolios.

In Figure 2, we visualize the mean-variance efficient frontier for Industry 100% and Industry 50% & Safe asset 50%, respectively, using the distribution of optimal pairs of risk-return.[10] We find that including safe assets in the portfolio moves a frontier to an area with significantly lower volatilities. For the global minimum variance point, the volatility is decreased by almost 50% when we add safe assets. This suggests that safe assets definitely provide the risk diversification role in our portfolio strategy. In addition, REIT (return = 4.116%, volatility = 9.116%) is consistently located under dominated areas, indicating that both strategies provide more efficient portfolio gains than an investment with only REITs.

We further investigate which industries and safe assets strongly contribute to the portfolio gains. To this end, we plot the average weight of mainly selected assets for the Industry 100% and Industry 50% & Safe asset 50% strategies in Figure 3. Panel A presents the average weight based on the minimum variance approach. As shown, Beer, Util, and Food, on average, account for over 10% of portfolio weight, indicating that these three industries occupy almost 50% of the industry portfolio. When safe assets are included, Beer, Util, and Food in "B.IND50%" consistently show higher weights than other industries. This suggests that certain industries could frequently provide a haven for REITs.[11] For the safe assets in "B.SA50%", the U.S. bond receives the largest allocation, followed by the JPY and gold. The strong contribution of the U.S. bond is consistent with the theoretical study of Elkamhi and Stefanova

[10] As we separately impose the weight limit of 50% on industry and safe asset set, the efficient frontier of Industry 50% & Safe asset 50% does not necessarily extend the frontier line of Industry 100%.

[11] However, it is worth noting that those industries in top ranked do not necessarily get similar magnitude of allocation over the sample period.



Note: This figure shows bar plots for the average portfolio allocation on industries and safe assets. Based on quarterly portfolio allocation across assets for minimum-variance, tangency portfolio, and equal-weight schemes, we obtain the average allocation percentage and rank for top 5 industries for Industry 100% ("A.IND100%") and top 5 industries and top 3 safe assets for Industry 50% & Safe asset 50% ("B.IND50% and B.SA50%").

Figure 3. Asset allocation

(2015), who document the substantial portfolio rebalancing toward less risky assets.

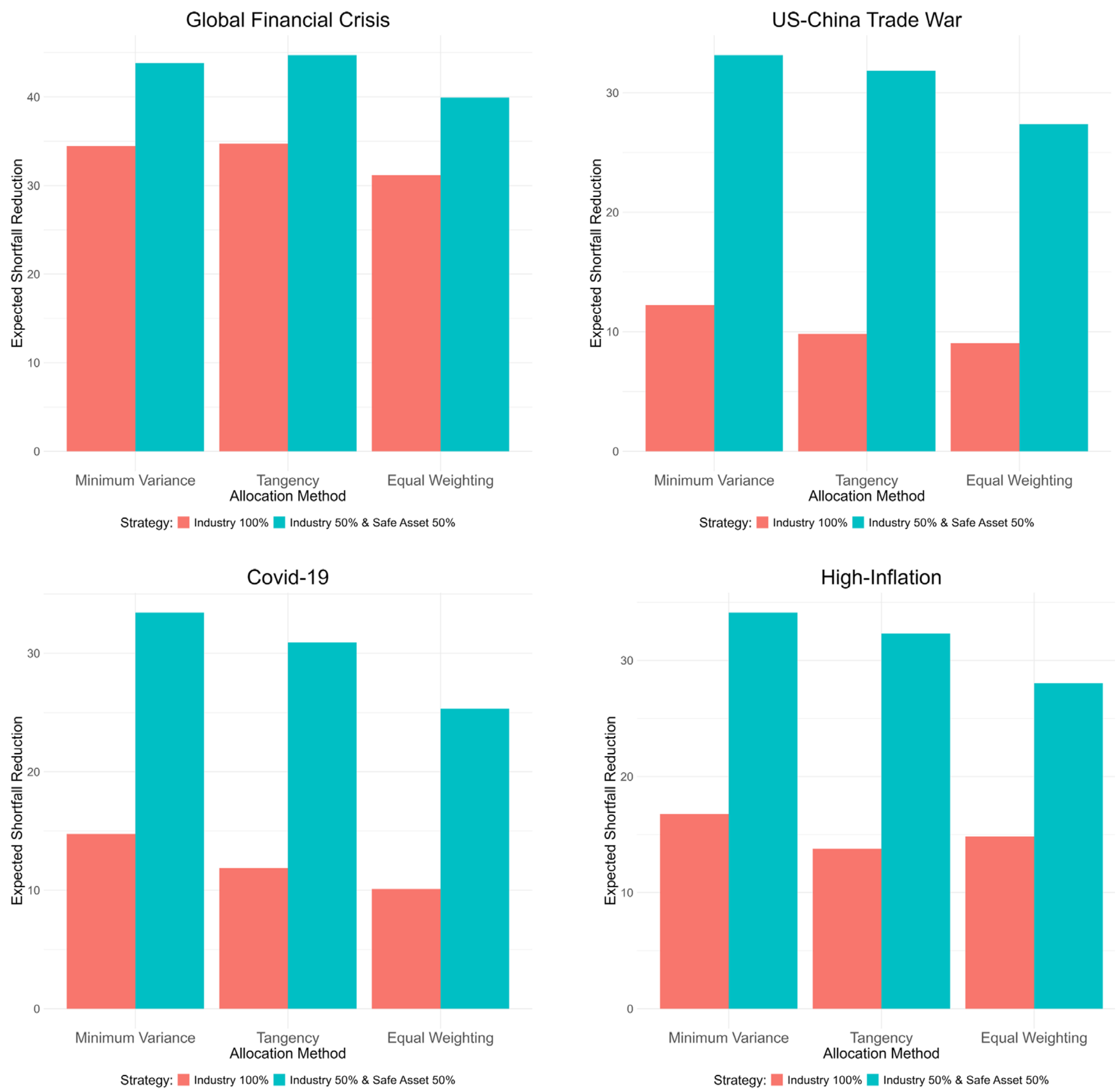
In the tangency portfolio of Panel B, Beer, Util, and Food are still important contributors to the portfolio composition. In addition, the smoke industry accounts for a large proportion under the tangency weight scheme. For safe assets in "B.IND50%", the U.S. bond remains the most important component in the minimum variance portfolio. The impact of the U.S. bond suggests that the U.S. bond is a primary tail risk buffer for the U.S. REIT market. Finally, Panel C shows that Beer, Food, and Smoke are major contributors to the equal-weight scheme. The U.S. bond does not show much greater weight than other safe assets, as shown in the other two weight schemes. A possible explanation is that the equal-weight approach ignores return variance, which plays a central role in determining portfolio weights under the minimum-variance and tangency strategies.

4.2. Time-varying gain

Exploring time-varying gains allows us to assess whether the flight-from-loss strategy remains effective under different macro-financial conditions, particularly during episodes of heightened volatility or systemic stress. Since asset co-movements and risk premia fluctuate over time, evaluating performance across distinct periods helps validate the robustness and practical applicability of the strategy (Fama & French, 1997; Lewellen & Nagel, 2006). This section identifies when diversification benefits are most pronounced and whether certain environments amplify or diminish the strategy's effectiveness.

We first explore risk reduction benefits throughout different macroeconomic regimes. Figure 4 examines whether the flight-from-loss strategy retains its effectiveness across different macroeconomic crises by measuring the expected shortfall (ES) reduction achieved under various allocation methods. The four panels represent distinct economic regimes: the Global Financial Crisis (2007–2012), the US-China Trade War (2018–2019), the COVID-19 pandemic (2020–2021), and the recent High-Inflation period (2022–2023). For each regime, the figure presents the out-of-sample risk reduction of the two portfolio strategies–Industry 100% and Industry 50% & Safe asset 50%–with three allocation methods: minimum variance, tangency portfolio, and equal weighting.

The Industry 100% strategy alone achieves meaningful tail risk reduction across all crisis regimes by reallocating capital to sectors that historically outperform during REIT downturns, with particularly strong performance during the Global Financial Crisis and COVID-19 periods. Optimi-



Note: This figure presents the out-of-sample reduction in expected shortfall for two portfolio strategies–Industry 100% and Industry 50% & Safe asset 50%–across four major macroeconomic regimes: the Global Financial Crisis (2007–2012), US–China Trade War (2018–2019), COVID-19 pandemic (2020–2021), and the recent High-Inflation period (2022–2023). Each panel shows the expected shortfall reduction by allocation method: minimum-variance, tangency, and equal-weighting. Results are expressed as percentage reductions of the expected shortfall relative to a REIT-only benchmark.

Figure 4. Risk hedging effectiveness across varying economic regimes

zation-based allocations, such as minimum-variance and tangency, consistently outperform equal-weighting, underscoring the importance of proper weighting. However, its effectiveness declines under high inflation, likely due to elevated cross-industry correlations, and equal-weighting remains the least effective. Overall, while less robust than strategies incorporating safe assets, the Industry 100% strategy still provides valuable, regime-sensitive downside protection through targeted sector selection. The Industry 50% & Safe asset 50% strategy consistently outperforms the industry-only approach across all crisis regimes and allocation methods, demonstrating the strong tail risk mitigation benefits of including safe assets like government bonds and gold. This advantage is most pronounced during severe stress periods such as the Global Financial Crisis and COVID-19, and notably, even the equal-weight allocation performs substantially better with safe assets included.

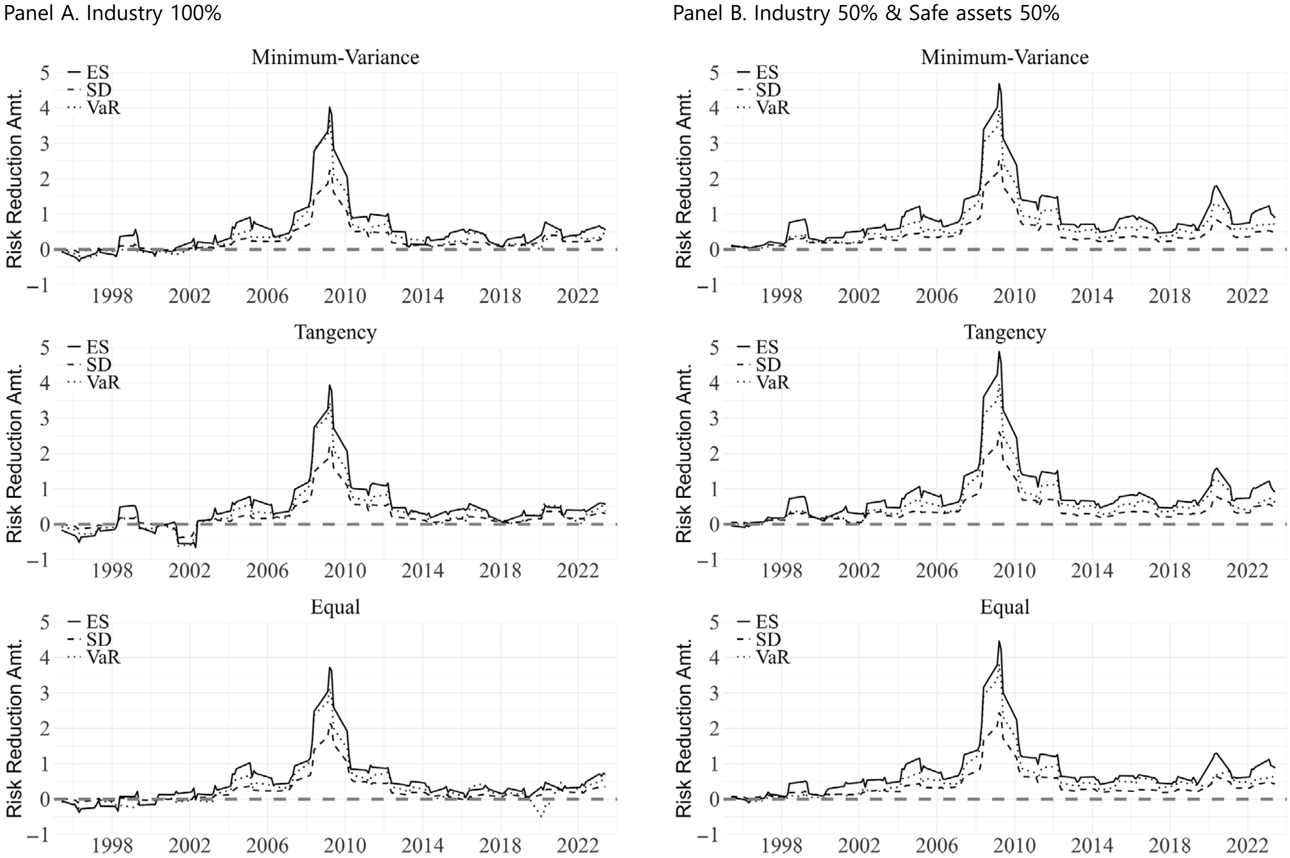
We further examine the diversification gains during the Global Financial Crisis – a period marked by unprecedented market dislocation and heightened asset return volatility. Table 3 presents the performance of the flight-from-loss strategy during the 2007Q1–2012Q2 crisis period, covering the subprime and European debt crises. In Panel A, the Industry 100% strategy shows robust tail risk reduction, with ES reductions of 34–35% across methods and Sharpe ratio growth exceeding 40% for optimized portfolios, especially the tangency allocation. Panel B further shows that incorporating safe assets significantly enhances effectiveness: all strategies achieve over 39% ES reduction, and even the equal-weight portfolio sees substantial improvements in both risk and Sharpe ratios. These results confirm that the strategy remains highly effective during systemic stress, particularly when safe assets are included.

Finally, Figure 5 illustrates the evolution of risk reduction over time, comparing the daily differences in risk measures between the REIT benchmark and the diversified portfolio strategies. Panel A shows that risk reduction is most significant during crisis periods, such as the global financial crisis. Outside of these volatile periods, the strategy still provides consistent but less pronounced risk mitigation, especially after 2000. The lower impact observed before 2000 can be attributed to the nature of REIT holdings during the 1990s, which were primarily focused on core commercial real estate assets that generated stable rental income with limited price fluctuations. Panel B demonstrates an even stronger and more consistent risk reduction effect. Including safe assets further enhances the diversification benefits, particularly during extreme market stress. The strategy effectively mitigated risk not only during the global financial crisis but also during the COVID-19 market collapse, suggesting its robustness in protecting portfolios during periods of heightened uncertainty. Overall, both strategies show substantial risk reduction during crisis periods, with Industry 50% & Safe asset 50% providing broader protection across time. This evidence reinforces the value of incorporating both industry assets and safe-haven assets to manage tail risk, especially when market conditions are volatile.

Table 3. Diversification benefits during crisis periods

	Min-var	Tangency	Equal
Panel A. Industry 100%			
RD_{vol}	36.030	36.665	34.38
RD_{VaR}	36.582	36.375	33.35
RD_{ES}	34.461	34.724	31.186
SG_{vol}	46.147	50.018	11.488
SG_{VaR}	47.419	49.333	9.765
SG_{ES}	42.648	45.556	6.314
Panel B. Industry 50% & Safe asset 50%			
RD_{vol}	44.302	44.815	41.19
RD_{VaR}	44.418	44.874	41.005
RD_{ES}	43.834	44.732	39.929
SG_{vol}	33.534	50.467	24.023
SG_{VaR}	33.811	50.629	23.633
SG_{ES}	32.420	50.241	21.419

Note: This table reports the portfolio benefits from the flight-from-loss approach for crisis periods (2007Q1–2012Q2) with three different allocation schemes: minimum variance ("Min-var"), tangency portfolio ("Tangency"), and naive equal weight ("Equal"). Panels A and B present results for the Industry 100% and Industry 50% & Safe asset 50% strategies, respectively. RD_{vol}, RD_{VaR}, and RD_{ES} represent the percentage reduction in volatility, value-at-risk, and expected shortfall, relative to the REIT benchmark. SG_{vol}, SG_{VaR}, and SG_{ES} denote Sharpe ratio growth rates based on the same risk measures. Risk reduction and Sharpe ratio growth are presented as percentages (%).



Note: This figure illustrates the time-series evolution of out-of-sample risk reduction amounts (in percentage points) for the Industry 100% and Industry 50% & Safe asset 50% strategies, across three risk measures: expected shortfall (ES), standard deviation (SD), and value-at-risk (VaR). Each panel corresponds to a specific allocation method – minimum-variance, tangency, or equal-weight. Risk reduction is computed as the difference in risk between the REIT-only portfolio and the diversified portfolio. The sample period is January 1993 to December 2023.

Figure 5. Time-varying risk reduction effects

5. Robustness

In this section, we conduct various robustness checks. First, we investigate whether our portfolio strategies provide better performance than diversified portfolios with assets sorted randomly instead of using ranking methods. Second, we examine whether our rank method based on the flight-from-loss is stronger than two alternative rank schemes: downside correlation and downside beta. Third, we explore how our results are robust to changes in various parameters.

5.1. Placebo test

While the portfolio strategy has demonstrated effective diversification against REIT risk, particularly during crises, there remains a possibility that the observed benefits are driven by the portfolio construction process itself rather than the specific selection of industries and safe assets through the rank-based flight-from-loss method. In other words, the benefits could stem from the weighting schemes (minimum-variance, tangency, and equal-weight) rather than the intentional selection of defensive assets. To test this, a placebo test was conducted by randomly selecting five industries (and three safe assets for the Industry 50% & Safe asset 50% strategy) rather than using the rank-based selection. This process was repeated 1,000 times, with the average performance reported in Table 4, along with the 5th and 95th percentile ranges of portfolio gains.

Panel A (Industry 100% Strategy) reveals a substantial drop in risk reduction when industries are randomly selected. For example, the minimum-variance strategy achieves less than a 15% reduction in tail risk, compared to the significantly higher reductions observed with the rank-based strategy. Sharpe ratio improvements are particularly diminished, with some results turning negative, indicating that randomly selected assets combined with REIT do not provide the same level of portfolio efficiency. Panel B (Industry 50% & Safe asset 50% strategy) shows a similar pattern, though the inclusion of safe assets slightly mitigates the decline in risk reduction. While risk reduction remains lower than the rank-based results, it is somewhat preserved due to the defensive nature of safe assets. However, Sharpe ratio growth is still significantly reduced, confirming the importance of asset selection based on performance during REIT downturns.

Table 4. Placebo tests from random simulation

	Min-var	Tangency	Equal
Panel A. Industry 100%			
RD_{vol}	15.348	12.806	11.066
	[13.911,16.712]	[11.064,14.464]	[10.048,12.102]
RD_{VaR}	14.449	10.959	9.53
	[12.699,16.255]	[8.691,13.068]	[8.051,11.035]
RD_{ES}	13.801	11.287	9.639
	[11.852,15.764]	[9.183,13.311]	[8.419,10.903]
SG_{vol}	0.192	1.072	–3.769
	[–8.543,8.231]	[–8.307,10.138]	[–9.796,1.460]
SG_{VaR}	–0.861	–1.024	–5.403
	[–9.042,6.728]	[–9.780,7.276]	[–10.877,–0.744]
SG_{ES}	–1.607	–0.659	–5.288
	[–9.572,5.703]	[–9.527,7.857]	[–11.009,–0.345]
Panel B. Industry 50% & Safe asset 50%			
RD_{vol}	35.062	32.094	26.144
	[34.527,35.602]	[31.168,32.949]	[25.501,26.776]
RD_{VaR}	34.371	30.878	24.858
	[33.427,35.363]	[29.599,32.041]	[23.913,25.869]
RD_{ES}	34.507	31.506	25.320
	[33.674,35.286]	[30.300,32.605]	[24.534,25.138]
SG_{vol}	3.927	4.864	1.999
	[–1.084,8.734]	[–2.100,12.059]	[–3.186,7.098]
SG_{VaR}	2.833	3.019	0.253
	[–1.449,6.938]	[–3.409,9.562]	[–4.370,4.863]
SG_{ES}	3.047	3.963	0.873
	[–1.566,7.337]	[–2.601,10.663]	[–4.022,5.725]

Note: This table reports the placebo test results based on random selection in the asset ranking process. For each simulation, we randomly select five industries (and three safe assets) for the Industry 100% and Industry 50% & Safe asset 50% strategies, then estimate portfolio gains–risk reduction and Sharpe ratio improvement–using the three weighting methods: minimum-variance ("Min-var"), tangency ("Tangency"), and equal-weight ("Equal"). This process is repeated 1,000 times, and the table presents the average portfolio gains along with the 5th and 95th percentiles in brackets. RD_{vol}, RD_{VaR}, and RD_{ES} denote the percentage reductions in volatility, value-at-risk, and expected shortfall, respectively. SG_{vol}, SG_{VaR}, and SG_{ES} represent the percentage growth in Sharpe ratios for the corresponding risk metrics. The sample period is January 1993 to December 2023.

These results confirm that the observed diversification benefits are not purely driven by the use of traditional portfolio weighting schemes. Instead, the rank-based selection of industries and safe assets plays a critical role in enhancing risk reduction and improving portfolio efficiency, supporting the effectiveness of the flight-from-loss methodology.

5.2. Alternative rank methods

We further assess whether our results are driven by alternative asset relationships during stress periods. We test two alternative downside dependence measures: downside correlation and downside beta (Ang & Chen, 2002; Ang et al., 2006). These metrics are calculated using standard correlation and beta estimates, conditional on the 5% extreme loss of REIT returns in each rolling window, capturing the degree of co-movement during severe market drops. Specifically, downside correlation and downside beta are defined as:

$$\text{Downside correlation} = \frac{E[(r_i-\mu_i)(r_{REIT}-\mu_{REIT}) \mid r_{REIT} < VaR^{5\%}_{REIT}]}{E[\sqrt{(r_i-\mu_i)^2(r_{REIT}-\mu_{REIT})^2} \mid r_{REIT} < VaR^{5\%}_{REIT}]};$$

$$\text{Downside beta} = \frac{cov[r_i, r_{REIT} \mid r_{REIT} < VaR^{5\%}_{REIT}]}{var[r_{REIT} \mid r_{REIT} < VaR^{5\%}_{REIT}]}, \quad (13)$$

where r_i and r_{REIT} are vectors of returns, and μ_i and μ_{REIT} are the mean returns for asset i and REIT, respectively. $VaR^{5\%}_{REIT}$ is the 5% threshold of value at risk in the empirical

Table 5. Alternative rank methods

	Downside correlation			Downside beta		
	Min-var	Tangency	Equal	Min-var	Tangency	Equal
Panel A. Industry 100%						
RD_{vol}	9.522	9.335	10.152	5.345	–0.638	1.523
RD_{VaR}	10.413	7.487	9.497	4.113	–1.988	–0.029
RD_{ES}	7.878	8.173	9.703	5.159	–1.043	0.941
SG_{vol}	7.726	4.625	4.034	7.492	16.416	1.861
SG_{VaR}	8.798	2.535	3.282	6.111	14.875	0.281
SG_{ES}	5.804	3.301	3.516	7.281	15.949	1.263
Panel B. Industry 50% & Safe asset 50%						
RD_{vol}	32.256	29.788	24.7	28.981	25.194	19.837
RD_{VaR}	32.354	28.69	24.271	28.444	24.641	19.275
RD_{ES}	31.619	29.255	24.272	28.302	24.993	19.337
SG_{vol}	6.877	9.938	8.667	4.275	19.889	7.535
SG_{VaR}	7.031	8.245	8.052	3.492	19.009	6.786
SG_{ES}	5.881	9.11	8.053	3.288	19.567	6.867

Note: This table reports portfolio gains based on two alternative asset selection methods: downside correlation and downside beta. In the first step of the strategy, industries and safe assets are ranked by either downside correlation or downside beta, measured conditional on the bottom 5% of REIT return realizations. Based on the top-ranked assets, portfolio gains are constructed using minimum-variance, tangency, and equal-weight strategies. RD_{vol}, RD_{VaR}, and RD_{ES} denote the percentage reductions in volatility, value-at-risk, and expected shortfall, respectively. SG_{vol}, SG_{VaR}, and SG_{ES} represent the percentage growth in Sharpe ratios for the corresponding risk metrics. The sample period is January 1993 to December 2023.

distribution of REIT for the rolling window period.[12] We then select the top 5 industries (and top 3 safe assets for Industry 50% and Safe asset 50%) that have shown the lowest downside correlation or downside beta with REITs. Based on the selected return series, we conduct the same procedures for the rest of the steps in Section 2.

Table 5 compares portfolio gains using downside correlation and downside beta. Panel A (Industry 100%) shows that both measures result in significantly lower risk reduction rates compared to our strategy, with the tangency portfolio providing the weakest risk reduction, indicating limited diversification benefits. Panel B (Industry 50% & Safe asset 50%) shows improved diversification when safe assets are included, though the gains remain lower than those achieved using our rank-based method. These results suggest that selecting assets based on return performance during extreme REIT losses offers superior diversification compared to rankings based on downside correlation or beta.

5.3. Robustness checks with different parameters

To ensure the robustness of our results, we tested our portfolio strategy under varying threshold levels. Since the choice of parameters in our portfolio construction could be somewhat arbitrary, it was important to evaluate whether our findings were consistent across different parameter sets rather than relying on a potentially optimized selection.

First, we investigate how diversification benefits vary with different threshold α for extreme loss estimation. Specifically, the threshold parameter α in Equation (1) varies from 5% to 50% with a 5% interval, expanding the focus beyond extreme losses. While the 5% threshold captures rare, severe losses, higher thresholds represent milder downside periods.

Table 6 summarizes the average risk reduction and Sharpe ratio growth across three risk measures: volatility, VaR, and ES. Risk reduction remains stable across all threshold levels, indicating that industries and safe assets with strong performance during REIT downturns consistently provide diversification benefits, even during moderate losses. However, Sharpe ratio growth declines as the threshold increases beyond the extreme loss point (5%), suggesting that assets performing well under severe REIT stress deliver more efficient risk-adjusted returns. The highest Sharpe ratio growth occurs at the 5% threshold, reinforcing the value of selecting assets based on extreme loss periods. While the minimum-variance and tangency portfolios maintain solid performance across all thresholds, the equal-weight strategy underperforms, highlighting the importance of optimized weighting schemes for effective risk management.

Second, we examine how diversification gains change with varying REIT allocation weights. While the previous analysis fixed REIT exposure at 50% to avoid potential over-concentration on particular assets through optimization, it is of interest to assess whether changing this proportion affects risk reduction and portfolio efficiency. This sensitivity analysis is relevant for REIT investors who

[12] Traditional methodologies of downside beta or correlation generally use 50% of threshold (e.g., Ang et al., 2006). However, we focus on extreme side of empirical distribution in the sense that our intuition is associated with changes in response to unusual or extreme shocks to REIT market.

Table 6. Varying benefits with threshold

Threshold α	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
Panel A. Industry 100%										
$\overline{RD}^{MV}$	22.377	21.951	21.246	20.657	21.216	20.520	21.265	20.995	20.042	21.077
$\overline{RD}^{TG}$	20.397	20.160	18.744	17.867	18.430	17.935	17.782	16.603	16.759	16.428
$\overline{RD}^{EQ}$	19.826	20.176	19.549	19.116	19.506	18.826	19.082	18.537	18.898	18.392
$\overline{SG}^{MV}$	3.739	1.338	2.544	–0.894	2.235	9.185	4.615	4.316	3.479	7.085
$\overline{SG}^{TG}$	11.780	1.861	–1.746	–5.559	–1.210	1.105	0.036	–2.990	–6.607	–1.527
$\overline{SG}^{EQ}$	–4.240	–6.113	–6.633	–7.062	–6.140	–2.821	–0.506	–4.384	–6.909	–7.627
Panel B. Industry 50% & Safe asset 50%										
$\overline{RD}^{MV}$	38.121	38.024	37.702	37.668	37.668	37.540	37.616	37.522	37.399	37.585
$\overline{RD}^{TG}$	36.392	35.913	35.290	35.010	35.229	35.006	34.757	34.319	34.405	34.354
$\overline{RD}^{EQ}$	32.371	32.544	31.939	31.698	32.034	31.424	31.757	31.404	31.458	31.228
$\overline{SG}^{MV}$	7.204	3.676	5.086	6.958	6.032	7.549	7.795	9.276	7.366	8.092
$\overline{SG}^{TG}$	12.414	5.164	2.321	–0.630	3.186	3.716	5.138	1.309	–1.833	4.038
$\overline{SG}^{EQ}$	0.249	–2.203	–2.447	–2.546	–1.614	1.846	3.930	1.551	–1.933	–1.841

Note: This table presents average portfolio gains across varying thresholds (α) used to define REIT tail risk, ranging from 5% to 50% in 5% increments. $\overline{RD}$ and $\overline{SG}$ denote the average risk reduction rate and Sharpe ratio growth, respectively, calculated for volatility, value-at-risk, and expected shortfall. Subscripts *MV*, *TG*, and *EQ* refer to the three weighting strategies: minimum-variance, tangency portfolio, and equal-weight, respectively. $\overline{RD}^{MV}$, $\overline{RD}^{TG}$, and $\overline{RD}^{EQ}$ represent the percentage reduction in risk, while $\overline{SG}^{MV}$, $\overline{SG}^{TG}$, and $\overline{SG}^{EQ}$ indicate the percentage improvement in Sharpe ratios. The sample period is January 1993 to December 2023.

Table 7. Varying benefits with REIT proportion

REIT Proportion	30%	40%	50%	60%	70%
Panel A. Industry 100%					
$\overline{RD}^{MV}$	25.738	24.556	22.377	19.386	15.581
$\overline{RD}^{TG}$	22.267	21.759	20.397	18.107	14.832
$\overline{RD}^{EQ}$	22.305	21.362	19.826	17.387	14.120
$\overline{SG}^{MV}$	–2.050	1.573	3.739	4.720	4.614
$\overline{SG}^{TG}$	8.809	10.913	11.780	11.344	9.650
$\overline{SG}^{EQ}$	–13.138	–8.269	–4.240	–1.448	0.210
Panel B. Industry 50% & Safe asset 50%					
$\overline{RD}^{MV}$	50.494	44.653	38.121	30.989	23.510
$\overline{RD}^{TG}$	46.700	42.064	36.392	30.054	23.300
$\overline{RD}^{EQ}$	41.662	37.401	32.371	26.832	20.666
$\overline{SG}^{MV}$	6.801	7.690	7.204	5.881	4.332
$\overline{SG}^{TG}$	12.773	13.584	12.414	10.376	8.086
$\overline{SG}^{EQ}$	–5.862	–1.985	0.249	1.459	1.693

Note: This table reports the average portfolio gains across different levels of REIT allocation, ranging from 30% to 70% in 10% increments. $\overline{RD}$ and $\overline{SG}$ denote the average risk reduction rate and Sharpe ratio growth, respectively, calculated for volatility, value-at-risk, and expected shortfall. Subscripts *MV*, *TG*, and *EQ* refer to the three weighting strategies: minimum-variance, tangency portfolio, and equal-weight, respectively. $\overline{RD}^{MV}$, $\overline{RD}^{TG}$, and $\overline{RD}^{EQ}$ represent the percentage reduction in risk, while $\overline{SG}^{MV}$, $\overline{SG}^{TG}$, and $\overline{SG}^{EQ}$ indicate the percentage improvement in Sharpe ratios. The sample period is January 1993 to December 2023.

Table 8. Varying benefits with selection number

	Industry number (N)					Safe asset number (M)				
	3	4	5	6	7	1	2	3	4	5
Panel A. Industry 100%										
$\overline{RD}^{MV}$	19.694	21.673	22.377	22.604	22.821					
$\overline{RD}^{TG}$	19.150	19.996	20.397	19.953	19.444					
$\overline{RD}^{EQ}$	17.297	18.801	19.826	19.811	19.556					
$\overline{SG}^{MV}$	0.161	–0.327	3.739	3.624	5.537					
$\overline{SG}^{TG}$	4.413	4.868	11.780	9.176	9.904					
$\overline{SG}^{EQ}$	–9.350	–8.841	–4.240	–4.328	–3.347					
Panel B. Industry 50% & Safe asset 50%										
$\overline{RD}^{MV}$	37.674	37.942	38.121	37.988	37.849	37.077	38.261	38.121	38.181	38.179
$\overline{RD}^{TG}$	35.942	36.171	36.392	36.127	35.778	36.826	36.811	36.392	36.127	36.049
$\overline{RD}^{EQ}$	35.169	33.686	32.371	31.100	29.788	25.927	30.053	32.371	34.005	35.348
$\overline{SG}^{MV}$	5.941	4.599	7.204	5.839	6.344	1.750	6.256	7.204	10.123	10.976
$\overline{SG}^{TG}$	9.919	8.515	12.414	11.205	11.682	6.429	10.770	12.414	14.184	15.317
$\overline{SG}^{EQ}$	–1.428	–2.075	0.249	–0.210	0.091	–2.777	–1.537	0.249	1.785	3.149

Note: This table presents average portfolio gains under varying selection sizes for industry and safe assets. The number of selected industries (N) ranges from 3 to 7, while the number of selected safe assets (M) ranges from 1 to 5. $\overline{RD}$ and $\overline{SG}$ denote the average risk reduction rate and Sharpe ratio growth, respectively, calculated for volatility, value-at-risk, and expected shortfall. Subscripts *MV*, *TG*, and *EQ* refer to the three weighting strategies: minimum-variance, tangency portfolio, and equal-weight, respectively. $\overline{RD}^{MV}$, $\overline{RD}^{TG}$, and $\overline{RD}^{EQ}$ represent the percentage reduction in risk, while $\overline{SG}^{MV}$, $\overline{SG}^{TG}$, and $\overline{SG}^{EQ}$ indicate the percentage improvement in Sharpe ratios. The sample period is January 1993 to December 2023.

may adjust their portfolio exposure based on individual risk preferences.

Table 7 presents average portfolio gains across volatility, VaR, and ES for varying REIT proportions (30% to 70%). Risk reduction declines as REIT exposure increases, reflecting less available capital for diversification. For example, in Panel A, the minimum-variance strategy reduces risk by 23.34% with a 30% REIT allocation but falls to 14.86% at 70% exposure. The effect is more pronounced in Panel B, where safe assets further amplify risk reduction, especially at lower REIT allocations. However, the marginal benefit of reducing REIT exposure diminishes at lower levels, showing a concave relationship where initial reductions offer stronger gains. For Sharpe ratio growth, the tangency portfolio consistently improves as REIT exposure decreases, while the minimum-variance approach shows similar benefits only when safe assets are included. The equal-weight strategy fails to show consistent improvement, underscoring the importance of optimization-based methods for effective diversification.

Finally, we investigate how the number of selected assets affects our results in Table 8. We apply varying numbers of industries and safe assets selected into the optimal portfolio estimation to examine whether our results are robust to changes in these parameters. First, we adjust the number of industries N that are selected in the rank method from 3 to 7. As shown in both Panels A and B, changes in N do not significantly affect the portfolio gains. When we allow the number of safe assets M to vary from 1 to 5 in Panel B, overall portfolio benefits are relatively improved from when M is 3. However, all values of M still provide significant portfolio gains, except for the equal-weight scheme. The results from Table 8 suggest that our results are also robust to the selection number for portfolio compositions in the rank method.

5.4. Further robustness tests

To ensure the strategy's practical relevance for long-term investors, it is important to verify whether the observed diversification benefits persist beyond short-term horizons. To this end, we conduct an additional robustness test using out-of-sample portfolio returns over a horizon of eight future quarters. This approach allows assessment of whether the defensive asset selection continues to deliver tail risk reduction and efficiency gains over extended periods, rather than only in the immediate term. As reported in Panel A of Table 9, both the Industry 100% and Industry 50% & Safe asset 50% strategies exhibit substantial reductions in expected shortfall and positive Sharpe ratio improvements, particularly under the minimum-variance and tangency portfolio allocations. These results confirm that the strategy retains its risk-mitigating benefits even when evaluated over longer-term investment horizons.

In addition to long-horizon performance, it is also essential to mitigate concerns about the historical nature of the asset selection framework. To mitigate this concern, we employ a forward-looking predictive REIT return. Specifically, predictive returns are estimated by first conducting a time-series regression of REIT returns on market-wide risk factors–namely, the Fama-French three factors, momentum, and changes in the VIX index–over a rolling window of the past eight quarters:

$$r_t^{REIT} = \alpha + \beta_1 r_t^{MKT} + \beta_1 r_t^{SMB} + \beta_1 r_t^{HML} + \beta_1 r_t^{MOM} + \beta_1 \Delta VIX_t + \varepsilon_t. \quad (14)$$

Estimated parameters ($\hat{\alpha}$, $\widehat{\beta_1}$,..., $\widehat{\beta_5}$) from this rolling-window regression are then applied to contemporaneous market factor realizations to compute the following predictive REIT returns:

$$\hat{r}_t^{REIT} = \hat{\alpha} + \widehat{\beta_1} r_t^{MKT} + \widehat{\beta_2} r_t^{SMB} + \widehat{\beta_3} r_t^{HML} + \widehat{\beta_4} r_t^{MOM} + \widehat{\beta_5} \Delta VIX_t. \quad (15)$$

This forward-looking benchmark is then used to define REIT loss conditions and guide defensive asset selection. Unlike a purely historical loss-based definition, this method is based on expected market stress, aligning the strategy more closely with real-time expectations. As shown in Panel A of Table 9, results based on predictive REIT returns exhibit comparable levels of risk reduction and Sharpe ratio gains, thereby confirming the robustness and adaptability of the flight-from-loss strategy.

Another concern is that our selection method may not capture some industries undergoing bad performance over the past periods, giving rise to the potential survivorship bias in industry selection. To mitigate, we compute the excess return for each industry as the difference between its raw return and its historical average return. The mean excess return for the industry is calculated as follows:

$$R_{i,t}^{excess} = R_{i,t} - \mu_{i,t}, \quad (16)$$

where $R_{i,t}$ is the raw return of industry i at time t, $\mu_{i,t}$ represents the average return of industry i over the past eight quarters. This adjustment enables an evaluation of industry performance relative to its own historical trend, reducing the chance of bias from industry exclusion compared to other industries. Based on this approach, the results in Panel C of Table 9 show that the historically adjusted industry portfolios maintain substantial risk reduction and Sharpe gains.

Finally, we investigate how removing the ex-ante 50% / 50% split between industry and safe assets alters the flight-from-loss strategy's tail-risk performance by letting all assets compete in a single pool. To disentangle the marginal value of hedging effectiveness of each asset category, earlier analysis has imposed an ex-ante 50% / 50% cap between industry portfolios and canonical safe havens (e.g., U.S. Treasuries, gold, major reserve currencies). This symmetric split prevents the optimization from being swamped by low-volatility assets and lets us trace how much of the tail-risk hedge is delivered by equity sectors versus defensive assets. When the constraint is eliminated in Panel D of Table 9, expected-shortfall reduction becomes even larger, confirming that safe assets dominate when left unconstrained. When compared to the results of Industry 100% in Table 2, expected-shortfall falls by a further around 20%, underscoring the decisive contribution of safe assets once cross-asset competition is permitted.

Table 9. Further robustness checks with alternative approaches

	Min-var	Tangency	Equal
	(1)	(2)	(3)
Panel A. Long-term effect			
Industry 100%			
RD_{ES}	20.051	16.945	17.866
SG_{ES}	4.774	4.044	–0.409
Industry 50% & Safe Asset 50%			
RD_{ES}	36.229	34.256	31.036
SG_{ES}	4.705	6.289	3.781
Panel B. Forward-looking REIT returns			
Industry 100%			
RD_{ES}	22.510	21.380	21.392
SG_{ES}	8.577	5.348	–1.438
Industry 50% & Safe Asset 50%			
RD_{ES}	38.080	36.810	33.119
SG_{ES}	9.301	8.805	4.308
Panel C. Historically adjusted industry returns			
Industry 100%			
RD_{ES}	22.614	19.533	20.083
SG_{ES}	3.549	0.929	–5.088
Industry 50% & Safe Asset 50%			
RD_{ES}	38.021	35.789	32.610
SG_{ES}	6.306	4.043	–0.249
Panel D. No split between Industry & Safe asset			
RD_{ES}	45.764	40.122	40.513
SG_{ES}	11.071	11.650	4.052

Note: This table reports the gains from a diversified portfolio using alternative approaches. Panel A uses the out-of-sample returns using 8 quarters in the future to investigate the long-term hedging effectiveness. Panel B utilizes alternative REIT returns for forward-looking asset selection. Specifically, predictive REIT returns are employed based on the 8-quarter rolling-window time-series regression with market factors. Panel C employs historically adjusted industry returns for industry selection. Historical adjustment indicates the deviation of returns from the historical average returns over the last 8 quarters. Panel D presents the results using a single asset pool where industry and safe assets are not split like 50%:50%. RD_{ES} is risk reduction for the expected shortfall, while SG_{ES} is the Sharpe ratio growth rate based on the expected shortfall. The sample period is January 1993 to December 2023.

5.5. External validity

The robustness tests previously conducted indicate that the flight-from-loss strategy consistently offers strong diversification benefits for REIT investors, particularly in managing tail risk. To further validate its broader applicability, we extended the strategy to all Fama-French 30 industries. For each industry, we designated it as the target asset while using the remaining 29 industries (and six safe assets) for diversification under both the Industry 100% and Industry 50% & Safe asset 50% strategies. This step was essential to ensure that the observed benefits were not limited to the REIT market alone but could be generalized across different sectors.

Table 10 reports the results, revealing considerable variation in diversification gains across industries. For the Industry 100% strategy, the highest risk reduction was observed in Coal, Steel, and Mines, while Food, Utilities (Util), and Household (Hshld) showed weaker results. Sharpe ratio growth followed a similar pattern, with Books, Steel, and Other industries ranking highest, while Beer, Household (Hshld), and Utilities (Util) underperformed. On average, the risk reduction rate and Sharpe ratio growth were 25.37% and 41.64%, both exceeding the results observed

Table 10. External validity from other industries

Industry	Industry 100%						Industry 50% & Safe asset 50%					
	$\overline{RD}^{MV}$	$\overline{RD}^{TG}$	$\overline{RD}^{EQ}$	$\overline{SG}^{MV}$	$\overline{SG}^{TG}$	$\overline{SG}^{EQ}$	$\overline{RD}^{MV}$	$\overline{RD}^{TG}$	$\overline{RD}^{EQ}$	$\overline{SG}^{MV}$	$\overline{SG}^{TG}$	$\overline{SG}^{EQ}$
Food	7.068	6.174	4.945	16.783	16.300	–4.801	32.015	29.437	23.468	14.428	13.372	4.697
Beer	14.939	14.064	12.627	9.015	8.730	–7.755	35.612	33.453	28.388	15.991	10.649	1.936
Smoke	27.638	25.973	25.706	23.937	23.591	–2.281	41.111	39.060	36.257	20.221	17.226	5.618
Games	33.305	32.733	32.462	43.731	46.469	33.592	43.270	42.551	40.034	34.942	36.476	29.814
Books	26.338	24.729	25.286	63.028	62.945	50.052	40.194	38.525	35.725	44.269	48.895	46.428
Hshld	13.297	9.754	11.218	16.688	16.939	1.988	34.235	31.724	27.201	14.075	19.572	7.527
Clths	30.214	28.411	28.718	41.041	40.654	28.411	41.932	40.407	38.026	32.447	34.572	28.549
Hlth	19.838	17.900	17.402	25.252	16.439	9.769	36.905	34.771	30.649	20.431	16.881	14.662
Chems	26.950	25.669	25.329	33.594	35.698	18.297	40.767	39.196	35.761	29.630	30.802	20.932
Txtls	32.919	31.764	31.364	84.858	87.660	68.769	43.035	41.977	39.498	60.715	65.222	58.543
Cnstr	28.450	26.947	26.985	29.198	26.694	17.562	40.819	39.377	36.642	23.569	23.623	19.468
Steel	36.540	35.817	35.032	56.666	60.739	41.499	44.609	43.889	41.497	43.036	41.181	38.153
FabPr	30.667	29.337	28.132	30.034	28.842	15.781	41.849	41.036	37.773	21.537	24.220	17.125
ElcEq	30.135	29.408	29.253	32.034	26.494	17.737	41.805	41.037	38.200	25.204	21.765	19.637
Autos	35.334	34.681	33.866	47.471	47.004	28.887	44.251	43.535	40.976	31.133	36.557	28.634
Carry	28.841	26.890	27.264	29.559	19.722	15.895	41.430	39.773	37.087	22.848	21.000	18.281
Mines	35.963	33.397	34.697	61.329	37.808	52.899	43.940	42.663	41.092	42.338	29.145	42.783
Coal	43.104	42.523	42.334	41.402	29.518	29.196	47.275	46.841	45.711	22.854	19.788	22.120
Oil	31.966	29.096	29.821	47.578	31.536	24.802	42.863	40.668	38.568	33.107	24.649	23.726
Util	13.702	11.445	11.606	–0.979	–1.516	–7.507	34.624	32.561	27.756	11.229	11.062	–0.758
Telcm	22.382	22.158	22.132	59.745	54.172	41.614	38.538	37.427	33.641	43.205	43.655	41.426
Servs	28.815	27.872	28.159	34.147	31.499	23.555	41.479	39.972	37.276	24.878	25.716	22.641
BusEq	33.251	32.544	31.592	33.401	35.882	19.609	43.411	42.339	39.740	24.015	28.746	21.238
Paper	20.332	17.336	18.788	42.643	34.068	19.360	37.764	35.724	31.841	33.555	31.796	25.111
Trans	27.391	25.794	25.965	29.629	30.393	16.831	40.779	39.266	36.274	23.114	28.605	21.150
Whlsl	20.801	19.257	18.737	31.446	32.476	23.053	37.337	36.162	32.040	27.544	28.422	24.480
Rtail	25.344	23.895	23.312	22.896	20.668	15.447	39.727	38.382	34.601	21.429	17.457	16.416
Meals	22.574	20.492	20.901	20.889	15.876	8.690	38.679	36.755	33.390	16.937	14.632	13.615
Fin	27.447	27.096	25.863	40.690	31.712	19.720	40.904	40.048	36.408	26.732	27.403	22.142
Other	22.944	21.084	20.717	73.292	57.073	42.322	38.509	37.096	33.138	47.664	43.831	42.590
Average	26.616	25.141	25.007	37.367	33.536	22.100	40.322	38.855	35.622	28.436	27.897	23.290

Note: This table reports the average portfolio gains for each of the Fama-French 30 industries when applying the flight-from-loss strategy. For each industry, the strategy treats it as the target asset while using the remaining 29 industries (and safe assets) as diversifiers. $\overline{RD}$ and $\overline{SG}$ denote the average risk reduction rate and Sharpe ratio growth, respectively, calculated for volatility, value-at-risk, and expected shortfall. Subscripts *MV*, *TG*, and *EQ* refer to the three weighting strategies: minimum-variance, tangency portfolio, and equal-weight, respectively. $\overline{RD}^{MV}$, $\overline{RD}^{TG}$, and $\overline{RD}^{EQ}$ represent the percentage reduction in risk, while $\overline{SG}^{MV}$, $\overline{SG}^{TG}$, and $\overline{SG}^{EQ}$ indicate the percentage improvement in Sharpe ratios. The sample period is January 1993 to December 2023.

in the REIT market. When safe assets were introduced under the Industry 50% & Safe asset 50% strategy, the risk reduction improved further, confirming the critical role of defensive assets in risk management. These findings suggest that the flight-from-loss strategy provides reliable diversification benefits across a range of industries, not just the REIT market, making it a versatile approach for portfolio optimization and tail risk management.

While the flight-from-loss strategy demonstrates consistent out-of-sample performance and robustness across crises, it remains subject to several important limitations. First, the approach relies on historical co-movements to identify defensive assets, implicitly assuming that the tail dependence structure across REITs, industry equities, and safe-haven assets remains stable–an assumption that may not hold under regime shifts or during novel crisis scenarios. Second, the strategy presumes consistent market liquidity for reallocation, which could be constrained during periods of systemic stress. Finally, we caution readers that future systemic shocks–particularly those driven by emergent risks such as geopolitical fragmentation, climate-induced disruptions, or AI-related market dislocations–may differ from past events, thereby limiting the external validity of historical patterns. Nevertheless, by documenting a transparent and empirically validated allocation rule, this study offers a practical starting point for managing tail risk in REIT portfolios.

6. Conclusions

This study introduces a novel portfolio strategy, the “flight-from-loss” approach, aimed at diversifying REIT tail risk by reallocating capital to assets that have historically shown stronger performance during extreme losses in the REIT market. Empirical results demonstrate that the strategy significantly reduces tail risk–by approximately 20% for industry-only portfolios and over 30% when combining industry assets with safe assets–while enhancing portfolio efficiency through increased Sharpe ratios. The benefits are particularly pronounced during periods of market turmoil when the demand for tail risk protection is greatest. We further document that similar or stronger portfolio gains can be achieved for most other Fama-French 30 industries, suggesting our approach can be generalized for ordinary risk management and portfolio allocation purposes.

Our flight-from-loss strategy may be particularly practical for retail investors. This group is a major component of REIT ownership and often holds underdiversified portfolios, making them more vulnerable to left-tail shocks. As retail investors can face challenges in reallocating portfolios swiftly during market downturns, our systematic approach–which prepares in advance based on historical downside relationships and requires only quarterly rebalancing–offers an implementable, low-turnover solution. The strategy’s design, which restricts portfolios to long-only positions, further aligns with the practical constraints typically faced by this investor group. However, investors should be mindful of several real-world limitations. First, the strategy’s effectiveness hinges on historical performance patterns, implicitly assuming that the tail dependence structure across assets remains stable; this may not hold during unprecedented market regime shifts or novel crises. Second, the approach presumes consistent market liquidity for reallocation, which could be constrained during the periods of systemic stress when the strategy is needed most, potentially hindering its implementation. Transaction costs, while mitigated by the quarterly rebalancing framework, also remain a practical friction. Despite these considerations, this study offers a transparent and empirically validated allocation rule that serves as a practical starting point for managing concentrated tail risk.

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Disclosure statement

The author has no conflicts of interest to disclose.

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