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STOCK RETURN RECOVERY MEASUREMENT AND PORTFOLIO OPTIMIZATION

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Abstract. *This paper presents an exploration of portfolio optimization strategies, with a specific focus on integrating the Recovery Ratio as a novel metric for quantifying the time period of losses and the resilience of portfolios. Drawing from historical data of Thai blue-chip stocks (SET50 index), the study emphasizes the strategic inclusion of quick-recovery stocks to enhance portfolio performance, particularly during market downturns. A significant contribution of this research lies in integrating the Recovery Ratio into portfolio optimization models as an objective function or a constraint. Through empirical analysis, the study uncovers that despite appearing less risk-efficient on efficient frontiers, quick-recovery portfolios consistently outperform slow-recovery counterparts in backtests and forward tests. This finding underscores the necessity of incorporating recovery metrics alongside traditional risk measures for effective portfolio management in dynamic market environments.*
Keywords: Portfolio optimization, Time under water, Conditional value at risk

1. **Introduction.** The stability and growth of a nation's financial sector are integral to achieving sustainable economic development, aligning with global goals such as the Sustainable Development Goals (SDGs) [1]. Investments in the financial markets, particularly through debt and equity instruments, are vital for wealth creation and resource allocation [2]. The sustainability of stock markets relies heavily on their ability to recover swiftly and effectively from downturns, bolstering market stability, investor confidence, and overall financial system resilience. Efficient stock market recovery not only restores investor trust but also mitigates systemic risks and fosters market liquidity and efficiency. Understanding the dynamics of stock market recovery is paramount for policymakers, regulators, and market participants to enhance market resilience and sustainability [3].

Traditional portfolio optimization models such as mean-variance optimization [4] often overlook the duration of negative returns in risk evaluation, relying heavily on measures like volatility and Value-at-Risk (VaR). This oversight can lead to suboptimal investment decisions as recovery speed post-downturn significantly influences portfolio performance and opportunity cost. This research aims to bridge this gap by integrating a novel measure of stock return recovery speed into portfolio optimization models, enhancing risk-adjusted return assessments across recovery horizons.

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The primary objective is to develop a comprehensive framework integrating the time dimension into portfolio optimization, providing a more accurate assessment of risk-adjusted returns over different recovery horizons. This includes introducing a novel measure of stock return recovery and assessing its performance against traditional methods in capturing temporal risk aspects.

The study focuses on proposing a new measure of stock return recovery speed and its application in portfolio management using data from Thailand's SET50 index. Analyzing daily return data from 2000 to 2023 aims to derive a robust recovery speed measure capturing market rebound dynamics. The research assesses the effectiveness of incorporating this measure in portfolio optimization, comparing its impact on risk-adjusted returns and portfolio performance with traditional risk measures like volatility.

The research contributes to improved decision-making for portfolio managers and risk analysts by integrating the time dimension into risk measures, enhancing risk management practices, and aligning investment strategies with investor preferences. It addresses a critical gap in literature by highlighting the importance of time in risk measures, advancing portfolio optimization theory, and contributing to financial market sustainability by mitigating market collapse effects and fostering faster recoveries.

2. **Literature Review.** Stock return recovery is a fundamental aspect of finance, describing the process through which stocks regain their value following a period of decline. This phenomenon has garnered significant attention due to its profound implications for investors and the broader economic landscape. Academic exploration of stock return recovery encompasses various facets, shedding light on its dynamics and ramifications within financial markets.

One prevailing narrative in the literature emphasizes the resilience of stock markets, suggesting that they often rebound after significant downturns. This resilience is attributed to factors such as market stabilization and the restoration of investor confidence. [5] delves into this phenomenon, noting that lower volatility periods frequently coincide with swifter recoveries, contributing to market stability. Similarly, research by [6] indicates that stock returns tend to be more robust during phases of economic growth, with market crashes often followed by rapid recoveries. These findings collectively highlight the transient nature of market downturns, underlining long-term investment prospects amidst short-term challenges [7].

The duration required for stocks to fully recover from downturns exhibits significant variability, influenced by a myriad of factors including the severity of the downturn and prevailing economic conditions. [8] suggests an average recovery time of approximately six months for US stocks. Conversely, studies like those by [9] indicate recovery periods ranging from 1.4 to 6.2 years post-bear markets, showcasing the diverse timelines associated with recovery. Such variations underscore the complex interplay of factors in determining recovery durations and highlight the need for comprehensive analysis.

Measuring the speed of stock return recovery involves a multifaceted approach, scholars employ diverse methodologies to measure stock return recovery speed. Event analysis by [10, 11], nonparametric tests by [12, 13], dynamic factor models by [14, 15], time series analysis by [16, 17], and regression analysis by [18, 19] are among the techniques used. These approaches assess factors like stock price reactions to events, pre- and post-event stock behaviors, market dynamics, and statistical relationships to gauge recovery speed accurately.

It is noteworthy, however, that despite the extensive body of literature dedicated to studying stock return recovery, there remains a gap in research pertaining to its integration within portfolio optimization frameworks. Specifically, there is a paucity of studies that incorporate stock recovery time as a critical parameter in portfolio construction, allowing investors to factor in the "time under water" when formulating investment strategies. This gap presents an opportunity to introduce an alternative approach to measuring recovery speed, one that is aptly tailored for integration into optimization problems.

To address this gap, our research not only introduces a novel measure of recovery speed suitable for optimization framework integration but also presents an approach to portfolio optimization. By incorporating stock return recovery speed as a fundamental consideration, our methodology offers investors a comprehensive toolkit for constructing portfolios that are not only risk-aware but also time-sensitive, thus aligning investment strategies more closely with market dynamics and enhancing overall portfolio resilience. This approach represents a significant advancement in portfolio theory, providing practitioners with a nuanced framework that acknowledges the temporal dimension of market recovery in investment decision-making.

3. Methodology.

The research seeks to introduce a pioneering metric for assessing the effectiveness of stock return recovery, termed the "Recovery Ratio", and its utility in portfolio construction. Accordingly, the subsequent discussion will elaborate the concept and computational methodology underpinning the assessment of the Recovery Ratio for individual stocks. Subsequently, the integration of the Recovery Ratio into a portfolio optimization framework will be demonstrated.

3.1. Recovery Ratio.

The Recovery Ratio is calculated as the ratio of the recovery period to the time under water, providing a relative assessment of a stock's ability to rebound from periods of losses. To compute the Recovery Ratio, the recovery period is determined as the time taken for the stock's value to surpass its previous peak, following a drawdown. On the other hand, the time under water denotes the duration during which the stock's value remains below its previous peak level. For every instance of being underwater within the stock's entire time series, a distinct Recovery Ratio is calculated, enabling a granular analysis of recovery dynamics.

To propose the formula of stock return Recovery Ratio (RR), we refer to the terminologies stated in [20] (see illustration in Figure 1).

- Time under Water (TUW) – It is the greatest possible temporal distance between two peaks. In other words, it computes how long it takes an investor to recoup his or her investment.
- Maximum Drawdown (MD) – It is a common indicator of the most an investment may anticipate to lose (the distance between the previous peak to the current trough). It should be emphasized that there may be local and global maximum drawdowns across the whole time period.
- Period of Maximum Drawdown (PMD) – It is the amount of time it takes to get from the previous peak to the bottom.
- Period of Recovery (POR) – It is the amount of time it takes to rebound from a trough to the same level as the prior peak.

Our measure of stock return recovery, the Recovery Ratio (RR), is hence introduced as follows:

$$\mathrm{RR} = \frac{1}{N}\sum_{i=1}^{N}\frac{\mathrm{POR}_i}{\mathrm{TUW}_i}, \tag{1}$$

where N denotes the total number of times the stock has been under water in the time series and the index i indicates each TUW accordingly. According to the proposed formulation, RR is thus ranged between 0 and 1. A small value of RR implies a quick recovery

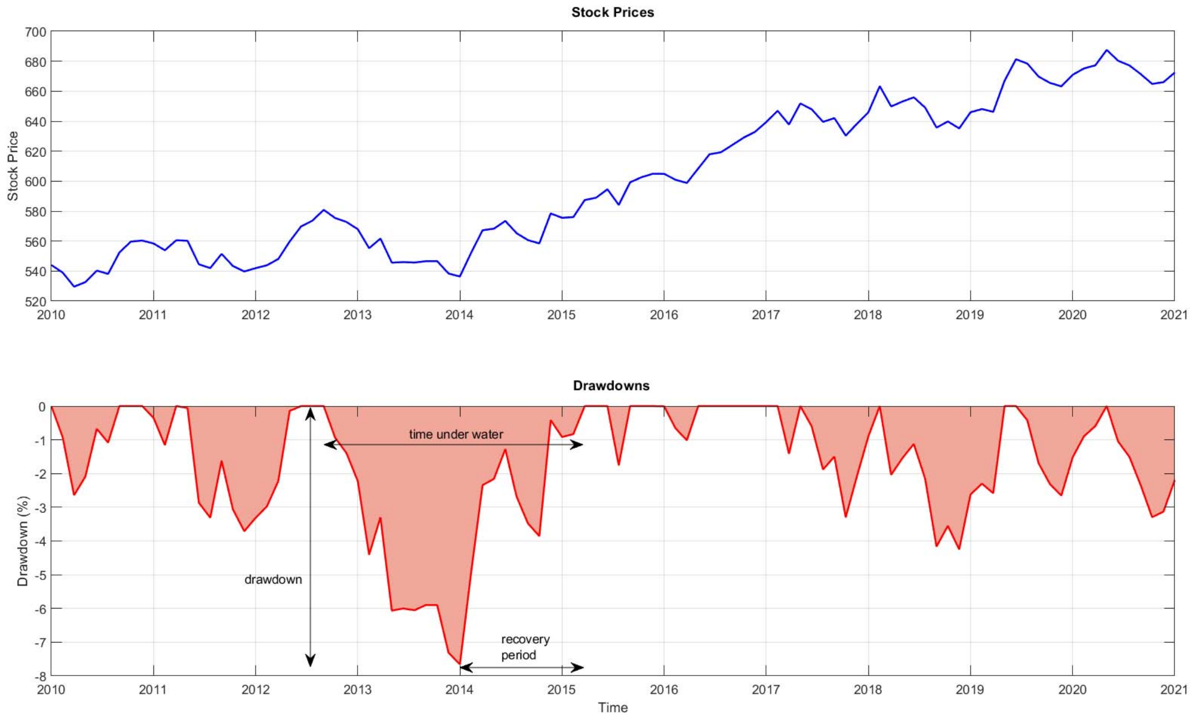


FIGURE 1. Components of time under water. The terminologies are what introduced in [20]. It should be noted that there may be multiple periods when the stock returns are under water over the whole time series.

stock, whereas a high number indicates a slow recovery stock.

The Recovery Ratio methodology presents distinct advantages compared to conventional metrics. It explicitly quantifies the speed and efficacy of recovery, offering valuable insights into a stock's resilience amid challenging market conditions. A higher Recovery Ratio indicates swifter rebound capabilities, reflecting the stock's ability to recover promptly following downturns. This feature complements traditional measures like drawdown analysis and risk-adjusted returns, which may lack comprehensive coverage of recovery dynamics.

Through the computation of multiple Recovery Ratios across different drawdown periods, this methodology facilitates a detailed and thorough assessment of a stock's recovery efficiency. This level of granularity empowers investors with deeper insights into recovery patterns, potentially uncovering underlying factors influencing the stock's recovery trajectory. Such insights are pivotal for informed investment decision-making and optimal portfolio construction.

A significant outcome of the Recovery Ratio methodology is the calculation of the average of these ratios. This average serves as a robust indicator of the stock's overall return recovery performance. A higher average Recovery Ratio signals consistent and efficient recovery across diverse market conditions. Consequently, stocks exhibiting higher average Recovery Ratios may be favored in portfolios seeking to manage downside risks while capitalizing on potential upsides.

The practical implications of this methodology are substantial for investors. The Recovery Ratio and its average offer valuable tools for portfolio construction and risk management strategies. Stocks with elevated average Recovery Ratios are likely to be considered favorable additions to portfolios, striking a favorable balance between risk mitigation and return optimization.

3.2. **Application of Recovery Ratio in a portfolio optimization problem.** We select a mean-Conditional Value at Risk (CVaR) as a standard optimization problem. Conditional Value at Risk (CVaR), also known as Expected Shortfall (ES), is chosen as a risk measure to emphasize on severe losses. Because Value at Risk (VaR) focuses on a certain percentile of the distribution (e.g., the 95th percentile), it does not give information regarding the severity of losses beyond that point. CVaR, on the other hand, takes account of the average of the worst-case situations above the set percentile. This is useful for quantifying tail risk, when extreme, unexpected occurrences can have a substantial influence on a portfolio.

The Recovery Ratio can be incorporated into an optimization problem as a constraint (Section 3.2.4) or as an objective function (Section 3.2.5).

3.2.1. *Notation.* Unless otherwise stated, the following notations are used throughout the report.

- Suppose there are a total of N securities with an initial price vector, $\mathbf{p}_0$, at time $t = 0$.
- Let $\mathbf{p}_1$ denote a random security price vector at date $t = 1$.
- Let f denote the Probability Density Function (PDF) of $\mathbf{p}_1$.
- Let $\mathbf{w}$ denote a vector of portfolio holdings that are chosen at date $t = 0$.
- Let $\mathbf{R}$ denote a vector of Recovery Ratios corresponding to the individual stock allocation $\mathbf{w}$.

3.2.2. *Optimization problem formulation.* From the notations given previously, the loss function, $l(\cdot)$, is then given by

$$l(\mathbf{w}, \mathbf{p}_1) = \mathbf{w}^{\mathrm{T}}(\mathbf{p}_0/\mathbf{p}_1 - 1). \tag{2}$$

Note that the loss function differs from a typical portfolio return calculation function in the sense that the loss function interprets positive values as losses and negative values as gains. Further, let $\Psi(\mathbf{w}, \alpha)$ = probability that the loss function does not exceed the threshold, α.

Since $\mathrm{VaR}_\beta(\mathbf{w})$ is the β-quantile of the loss distribution,

$$\Psi(\mathbf{w}, \mathrm{VaR}_\beta(\mathbf{w})) = \beta. \tag{3}$$

By mathematical definition, CVaR_β is an average of losses greater than VaR_β, hence

$$\mathrm{CVaR}_\beta = \frac{1}{1-\beta}\int_{l(\mathbf{w},\mathbf{p}_1) > \mathrm{VaR}_\beta(\mathbf{w})} l(\mathbf{w}, \mathbf{p}_1) f(\mathbf{p}_1) d\mathbf{p}_1.$$

It is, however, somewhat difficult for optimization because VaR is not formulated explicitly. Therefore, [21] proposes a function of CVaR for an optimization problem as

$$F_\alpha(\mathbf{w}, \alpha) = \alpha + \frac{1}{1-\beta}\int_{l(\mathbf{w},\mathbf{p}_1) > \alpha} (l(\mathbf{w}, \mathbf{p}_1) - \alpha) f(\mathbf{p}_1) d\mathbf{p}_1. \tag{4}$$

The above equation signifies that

$$\min_{\mathbf{w}\in\mathcal{W}} \mathrm{CVaR}_\beta(\mathbf{w}) = \min_{\mathbf{w}\in\mathcal{W},\alpha} F_\alpha(\mathbf{w}, \alpha),$$

where $\mathcal{W}$ is the subset of $\mathbb{R}^N$ denoting the set of feasible portfolios. We can thus optimize CVaR_β and compute the corresponding VaR_β by minimizing $F_\alpha(\mathbf{w}, \alpha)$ with respect to both $\mathbf{w} \in \mathcal{W}$ and α.

In practice, a probability density function, f, is discretized to ease numerical computation. Rather than working with f as a continuous function, a set of discrete probabilities

$\mathbf{p}_1^{(1)}, \ldots, \mathbf{p}_1^{(J)}$, where J is the set of contiguous intervals (bins) of discretized return distributions, is created to represent f instead. Consequently, $F_\alpha(\mathbf{w}, \alpha)$ is approximated with $\tilde{F}_\alpha(\mathbf{w}, \alpha)$ as follows:

$$\tilde{F}_\alpha(\mathbf{w}, \alpha) = \alpha + \frac{1}{J(1-\beta)} \sum_{j=1}^{J} \left(l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right) - \alpha \right)^+ . \tag{5}$$

In our setting above, $l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right)$ is linear so we can solve it using Linear Programming (LP) methods. $(x)^+ = x$ when $x > 0$ and $(x)^+ = 0$ otherwise.

3.2.3. *Standard mean-CVaR portfolio optimization.* Suppose there are a total of N securities with an initial price vector, $\mathbf{p}_0$, at time $t = 0$. Let $\mathbf{p}_1$ denote a random security price vector at date $t = 1$, f denote a PDF of $\mathbf{p}_1$ and $\mathbf{w}$ denote a vector of portfolio holdings that are chosen at date $t = 0$. The loss function at time $t = 1$ is given by Equation (2). We then set up a mean-CVaR portfolio optimization with the same formulation as Rockafellar and Uryasev [21] as follows:

$$\begin{aligned}
\min_{\alpha, \mathbf{w}, \mathbf{z}} \quad & \alpha + \frac{1}{J(1-\beta)} \sum_{j=1}^{J} z_j \\
\text{subject to} \quad & l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right) - \alpha \le z_j, \\
& z_j \ge 0, \\
& \mathbf{w} \in \mathcal{W},
\end{aligned} \tag{6}$$

where β is a confidence level of VaR (typically set as 0.95), J is the set of bins of the discretized return distributions, z_j indicate losses beyond the VaR level (α) in which the average of them signifies CVaR and $\mathcal{W}$ is a set of portfolio constraints.

3.2.4. *Standard mean-CVaR portfolio optimization with Recovery Ratio constraint.* In this formulation, the Recovery Ratio is incorporated into a constraint of the standard mean-CVaR optimization problem (6). The constraint specifies that the weighted Recovery Ratio of a portfolio must not exceed the threshold $\mathcal{R}$. Suppose that the threshold $\mathcal{R}$ is small, the portfolio will tilt its allocation toward quick recovery stocks. The optimization problem is therefore formulated as follows:

$$\begin{aligned}
\min_{\alpha, \mathbf{w}, \mathbf{z}} \quad & \alpha + \frac{1}{J(1-\beta)} \sum_{j=1}^{J} z_j \\
\text{subject to} \quad & l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right) - \alpha \le z_j, \\
& z_j \ge 0, \\
& \mathbf{w}^{\mathrm{T}} \mathbf{R} \le \mathcal{R}, \\
& \mathbf{w} \in \mathcal{W}.
\end{aligned} \tag{7}$$

3.2.5. *Minimized Recovery Ratio portfolio optimization.* This setting treats CVaR as a constraint and employs the Recovery Ratio as an objective function instead. The optimal allocation yields a portfolio with minimum Recovery Ratio. Accordingly, the optimization problem becomes

$$\min_{\mathbf{w}} \quad \mathbf{w}^{\mathrm{T}} \mathbf{R}$$

$$
\begin{aligned}
\text{subject to} \quad & \alpha + \frac{1}{J(1-\beta)} \sum_{j=1}^{J} z_j, \\
& l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right) - \alpha \leq z_j, \\
& z_j \geq 0, \\
& \mathbf{w} \in \mathcal{W}.
\end{aligned} \tag{8}
$$

Other constraints such as target return, e.g.,

$$
\sum_{j=1}^{J} l\left(\mathbf{w}, \mathbf{p}_1^{(j)}\right) + \mu = 0, \tag{9}
$$

where μ is a target return, could be added to avoid corner solutions. Employing the Recovery Ratio as an objective function or a constraint involves several trade-offs and considerations. When employed as an objective function, it has a direct impact on the optimization outcome, highlighting assets with high potential for recovery. As a constraint, it guarantees that a certain degree of recovery efficiency is satisfied while tolerating other optimization goals. The investor's preferences, risk tolerance, and desired balance between recovery efficiency and other portfolio objectives all influence the decision between the two techniques.

3.3. **Data description.** The dataset includes historical stock returns from the SET50 index, representing Thailand's top 50 stocks by market capitalization on the Stock Exchange of Thailand (SET). The dataset covers January 1, 2000, to May 31, 2023, with daily frequency. The index's constituents and data are sourced from the Stock Exchange of Thailand and Bloomberg terminal. To ensure statistical robustness, firms with a minimum five-year time series are included, starting before 2018. Details of the qualified stocks including the calculated Recovery Ratio are exhibited in Table 1 in the following section.

4. **Results and Discussions.** In synthesizing the results and engaging in a comprehensive discussion, this section contributes to the ongoing dialogue in financial literature regarding the practical implications of recovery dynamics on investment strategies. It clarifies not only the recovery speed (proxied by the Recovery Ratio) of individual stocks but also the strategic opportunities afforded by integrating recovery considerations into a portfolio optimization process. The ensuing discussion provides a contextualized understanding of the empirical results, facilitating a richer comprehension of the implications for both theoretical frameworks and practical investment decisions.

4.1. **Data handling.** The study analyzes stock returns of the SET50 index, representing the top 50 companies listed on the Stock Exchange of Thailand (SET), due to their strategic importance and market influence. The dataset, sourced from Bloomberg terminal, includes daily total returns (with dividends) from 1 January 2000 to 31 May 2023, providing a detailed view of long-term stock performance. The SET50 constituents, as of the first half of 2023, were obtained from the official SET website.

To ensure reliability and robustness, the dataset includes only firms with at least five years of return data and time series starting before 2017, extending through 31 May 2023. This selection captures a comprehensive and dynamic cross-section of corporate behavior over time. Ultimately, 36 stocks met these criteria (as shown in Table 1). Data cleaning includes removing duplicate entries, addressing missing data through interpolation for short gaps. Outliers are identified using z-scores, validated against known corporate

Table 1. Statistics of time spent when stock prices ascend from the trough and make their way to the same level as the previous peak (recovery). The recovery time is varied in each drawdown episode. The Recovery Ratio (RR) is the proportion of time spent for a stock to recover over an entire period of time under water. Stocks in the table are sorted by the Recovery Ratio. Source: authors' calculation.

Stock	Shortest recovery (days)	Longest recovery (days)	Average recovery (days)	Recovery Ratio
SCC	3	428	87.04	0.49
GPSC	7	214	55.50	0.50
SAWAD	3	318	53.50	0.50
KTC	3	940	81.80	0.51
KTB	5	585	231.00	0.51
AOT	2	862	71.14	0.51
HMPRO	2	258	30.03	0.52
DELTA	1	1,054	71.72	0.53
CBG	4	371	56.79	0.54
TISCO	2	431	64.04	0.54
BBL	2	747	79.31	0.54
KBANK	2	585	60.61	0.54
EA	3	817	103.87	0.54
COM7	2	105	22.53	0.55
GLOBAL	2	548	40.76	0.56
LH	2	987	115.82	0.56
INTUCH	2	795	119.08	0.56
BH	3	1,078	76.85	0.57
TU	1	360	68.32	0.57
CPN	3	671	46.67	0.57
CPF	3	208	27.94	0.57
TOP	2	2,162	270.56	0.57
MTC	2	221	30.65	0.57
PTTGC	6	420	95.29	0.58
BANPU	2	444	59.52	0.58
BDMS	2	495	56.96	0.58
CPALL	3	698	41.62	0.58
BTS	3	1,386	205.13	0.60
EGCO	3	931	73.25	0.60
CENTEL	1	489	68.12	0.60
PTTEP	1	529	138.18	0.63
MINT	2	937	74.26	0.63
RATCH	4	1,302	119.88	0.63
IVL	4	1,111	153.62	0.64
BEM	3	1,028	110.24	0.65
PTT	5	2,215	114.54	0.65

actions, and retained if deemed legitimate. Otherwise, they are winsorized at the 95th percentile to mitigate their impact on the analysis while maintaining data integrity.

4.2. **Recovery dynamics of stocks.** The following section provides the details pertaining to the recovery speed exhibited by individual stocks within the treated dataset in the previous section. Leveraging the Recovery Ratio (Section 3.1) as a discerning metric, the study unveils how various equities navigate and recuperate from periods of market downturns. Recovery statistics, encompassing key parameters such as recovery periods and time under water durations, afford insights into the resilience and efficiency of individual stocks in re-establishing their value following episodes of decline.

Table 1 examines recovery durations for stocks to emerge from Times under Water (TUW), focusing on the Recovery Ratio. Our analysis reveals diverse recovery times, ranging from one month to nearly a year, highlighting unique paths to stability. The Recovery Ratio distinguishes between swift and prolonged recoveries, crucial for understanding recovery pace. Empirical findings also show no pronounced differences or distinct clusters in Recovery Ratios across stocks, indicating a lack of clear categorization based on recovery efficiency.

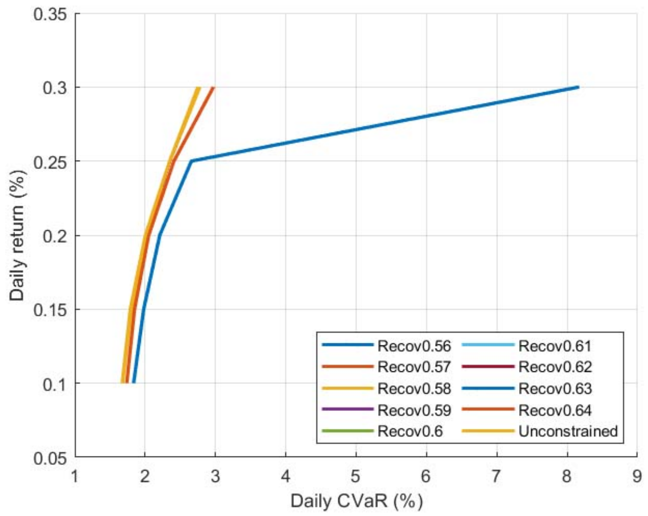
4.3. **Application of Recovery Ratio in portfolio allocation.** This section empirically explores using Recovery Ratios in portfolio construction, examining their impact as constraints and objectives in optimization models. We integrate Recovery Ratios as both constraints and objectives in optimization, setting recovery thresholds and shaping recovery-centric portfolios. These findings contribute to theoretical portfolio optimization and practical investment decision-making.

We introduce a mean-CVaR portfolio optimization problem to comprehensively capture tail risk. Constraints ensure a fully invested, long-only portfolio with a predefined return objective. Varying Recovery Ratio constraints guide optimization toward different recovery thresholds within the mean-CVaR framework, revealing their impact on risk-return profiles. The dataset is divided into in-sample (2000-2019) and out-of-sample (2020-2023) periods to test model robustness under diverse market conditions, including the COVID-19 pandemic.

4.3.1. *Recovery Ratio as a constraint.* This study systematically varies the Recovery Ratio from 0.56 to 0.64 to investigate its impact on the risk-return characteristics of portfolios, aiming to understand the dynamic relationship between recovery thresholds and efficient frontiers and revealing diverse risk-return trade-offs. To further assess the influence of recovery constraints, we include an "unconstrained" case where the Recovery Ratio is unrestricted in this and subsequent analyses, allowing a direct comparison of the effects of Recovery Ratios with traditional mean-CVaR portfolio optimization.

Figure 2 shows how Recovery Ratio constraints impact portfolio efficiency, revealing a reduction in efficiency with stricter constraints. The unconstrained frontier denotes the case where the Recovery Ratio is unrestricted. When the Recovery Ratio is below 0.56, the portfolio's Conditional Value at Risk (CVaR) range widens, indicating higher tail risk ranging from 2% to 8%. Conversely, relaxed Recovery Ratio constraints narrow the CVaR range to around 1.5% to 3%, suggesting reduced tail risks and smaller potential losses in more flexible portfolios. The Recovery Ratios ranging from 0.57 to 0.64 are closely clustered and can be observed as a singular frontier in our analysis.

4.3.2. *Recovery Ratio as a group divider.* In contrast to the previous subsection's focus on maintaining an aggregate Recovery Ratio within predefined levels, this investigation aims to categorize stocks into quick and slow recovery groups. This segmentation allows for a detailed analysis of their risk-return profiles along the efficient frontiers. This targeted



Daily return (%)	Daily CVaR (%) by Recovery Ratios									
	0.56	0.57	0.58	0.59	0.60	0.61	0.62	0.63	0.64	Unconstrained
0.10	1.84	1.74	1.68	1.67	1.67	1.67	1.67	1.67	1.67	1.67
0.15	1.98	1.85	1.80	1.79	1.79	1.79	1.79	1.79	1.79	1.79
0.20	2.21	2.05	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
0.25	2.66	2.41	2.35	2.35	2.35	2.35	2.35	2.35	2.35	2.35
0.30	8.17	2.97	2.78	2.75	2.75	2.75	2.75	2.75	2.75	2.75

FIGURE 2. (color online) Efficient frontiers at different Recovery Ratio limits. As the Recovery Ratio increases, the risk-return profile converges with the unrestricted Recovery Ratio (unconstrained) case. Source: authors' calculation.

evaluation aims to reveal the unique risk-return dynamics of portfolios constructed solely from quick and slow recovery stocks, contributing significantly to our understanding of recovery speed's impact on portfolio performance and risk management.

Using a Recovery Ratio threshold of 0.57, stocks are classified as quick or slow recovery, leveraging this metric for segregation. The threshold is empirically chosen as the midpoint of the observed Recovery Ratio range (0.49 to 0.65). This value serves as a pragmatic cutoff for distinguishing between quick and slow recovery stocks. Setting the threshold too high or too low would dilute the classification, thereby weakening the distinction between the two groups. By selecting the midpoint, we aim to maintain a balanced and meaningful separation between quick- and slow-recovery stocks. However, identifying an "optimal" cutoff that maximizes the distinction between these groups remains an open area for further research. Such an investigation could explore how variations in this threshold impact portfolio performance, particularly in different market environments or across various industries.

Figure 3 illustrates the risk-return profiles of portfolios from quick and slow recovery stocks. Quick recovery portfolios have wider tail loss ranges (3% to 10%) compared to slow recovery portfolios (2% to 3%), indicating higher potential losses in extreme events. This aligns with earlier findings, emphasizing the trade-offs between recovery efficiency and risk-return profiles in portfolio construction within financial markets.

4.3.3. *Backtesting.* The backtesting protocol examines optimal portfolios derived from an optimization framework using the Recovery Ratio as either a constraint or a group divider.

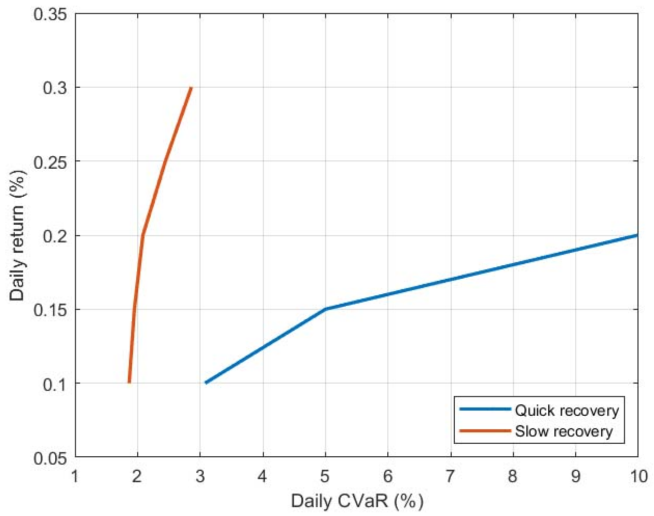


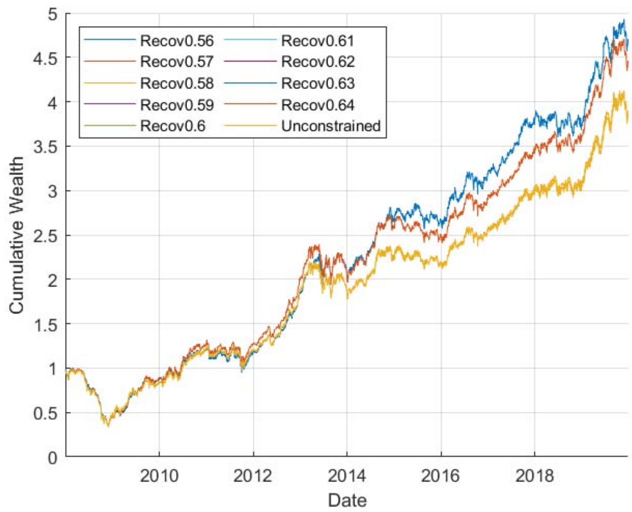
FIGURE 3. Efficient frontiers of the quick recovery and the slow recovery. The cutoff of the two clusters is based on the Recovery Ratio of 0.57. Source: authors' calculation.

It aims to explore how portfolios, optimized under different Recovery Ratio scenarios, have performed historically in dynamic market conditions. Analyzing cumulative wealth trends and drawdown durations provides insights into portfolio resilience, adaptability, and risk management effectiveness. To conduct a comprehensive backtesting, portfolios are strategically selected from the midpoint of each frontier in Figure 2, representing a balance between risk and return.

Modern Portfolio Theory (MPT) posits that higher-risk portfolios, as measured by CVaR, should yield higher returns, reflecting the fundamental trade-off between risk and reward. However, backtesting results challenge this assumption, showing that portfolios with the lowest Recovery Ratios – those expected to underperform due to less favorable risk-return trade-offs – actually achieve the highest cumulative returns. This divergence arises because traditional risk metrics like CVaR fail to account for the time portfolios spend in negative territory. By incorporating the Recovery Ratio, which captures the temporal dimension of risk, quick-recovery portfolios benefit from reduced time spent recovering from drawdowns as shown in Figure 4, leading to superior long-term performance. In contrast, portfolios with more relaxed Recovery Ratio constraints appear more efficient on the efficient frontier but ultimately underperform in cumulative return due to their prolonged recovery periods.

The table at the bottom of Figure 4 shows descriptive statistics. The metrics provide a comprehensive view of portfolio behavior under different constraints, including both return-based and risk-based measures. When Recovery Ratios exceed 0.59, portfolio characteristics closely resemble those of the unconstrained case, with little differentiation in performance metrics, except for volatility. However, the differences in volatility are marginal and unlikely to offset the deterioration in overall performance, underscoring the importance of integrating recovery speed into risk assessments alongside conventional metrics. This suggests that quick-recovery portfolios are better positioned to accumulate returns more effectively over time, challenging the conventional reliance on static risk-return metrics like CVaR.

The last metric of the descriptive statistics shows drawdown durations for portfolios with different Recovery Ratio constraints. Tighter constraints (average ratio 0.56) reduce



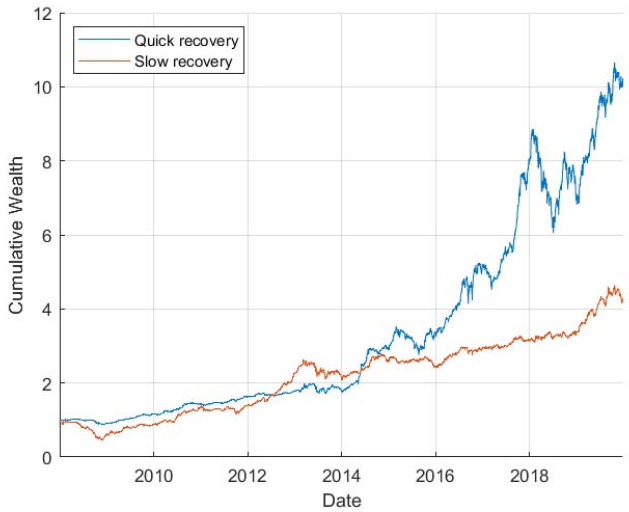
Descriptive statistics	Recovery Ratio									
	0.56	0.57	0.58	0.59	0.60	0.61	0.62	0.63	0.64	Unconstrained
Cumulative return (%)	369.98	344.97	289.13	284.45	284.45	284.45	284.45	284.45	284.45	284.45
Average return (%)	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Min return (%)	−9.55	−9.57	−9.92	−10.06	−10.06	−10.06	−10.06	−10.06	−10.06	−10.06
5th percentile (%)	−1.57	−1.58	−1.59	−1.60	−1.60	−1.60	−1.60	−1.60	−1.60	−1.60
Max return (%)	7.74	8.19	8.47	8.59	8.59	8.59	8.59	8.59	8.59	8.59
Volatility (%)	1.18	1.19	1.19	1.17	1.17	1.17	1.17	1.17	1.17	1.17
Sharpe ratio	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Max DD (%)	63.08	63.61	64.85	64.86	64.86	64.86	64.86	64.86	64.86	64.86
Max DD duration (day)	501	563	567	608	608	608	608	608	608	608

FIGURE 4. (color online) Cumulative wealth indices of efficient portfolios under different recovery constraints. Source: authors' calculation.

drawdown duration by nearly 100 days compared to more relaxed constraints (average ratio of 0.6 and over). This highlights the Recovery Ratio's pivotal role in portfolio resilience and rebounding from market downturns. The 3-month head start in return compounding underscores its impact on mitigating drawdowns and enhancing overall portfolio performance.

The analysis of portfolios from quick- and slow-recovery stocks in Figure 5 shows clear differences in backtest performance. Constrained Recovery Ratio optimization leads to an optimal blend of quick- and slow-recovery stocks, while exclusive optimization from either category results in more extreme outcomes. The bottom table of Figure 5 highlights the descriptive statistics of the quick and the slow recovery portfolios. The table shows that the quick-recovery portfolio outperforms the slow-recovery portfolio with a higher cumulative return (923.40% vs. 326.84%), better average return (0.08% vs. 0.05%), a higher Sharpe ratio (0.09 vs. 0.05), and a smaller maximum drawdown (−31.56% vs. −53.28%) over a shorter duration (308 vs. 542 days). Although the slow-recovery portfolio exhibits a slightly higher max return and lower volatility, the quick-recovery portfolio demonstrates superior overall performance and, most notably, faster recovery from losses. The nearly year-long difference in drawdown duration between the two portfolios underscores the critical temporal advantage of the quick-recovery portfolio, which contributes to its more favorable backtest outcomes.

4.4. **Forward testing.** In this section, we examine optimal portfolios in unfamiliar market conditions. Backtesting uses the same dataset as portfolio optimization, leading to



Descriptive statistics	Recovery group	
	Quick	Slow
Cumulative return (%)	923.40	326.84
Average return (%)	0.08	0.05
Min return (%)	−5.00	−7.53
5th percentile (%)	−1.42	−1.43
Max return (%)	5.74	7.85
Volatility (%)	0.99	1.04
Sharpe ratio	0.09	0.05
Max DD (%)	−31.56	−53.28
Max DD duration (day)	308	542

FIGURE 5. (color online) Cumulative wealth indices of the quick- and slow-recovery portfolios. Source: authors' calculation.

rare instances of poor performance due to portfolios being aware of past extreme events. Conversely, forward testing employs an unseen dataset, offering a more realistic assessment of portfolio adaptability to unforeseen market conditions. This shift enhances the findings' external validity, providing insights into portfolio robustness during novel market environments, including the COVID-19 outbreak and subsequent recovery, along with challenges like rising interest rates.

Figure 6 presents the cumulative wealth indices of portfolios under varying Recovery Ratio constraints, along with detailed descriptive statistics. The graph shows that portfolios with lower Recovery Ratios (e.g., 0.56 and 0.57) achieve positive cumulative returns, while portfolios with higher Recovery Ratios (above 0.59) and the unconstrained portfolio exhibit negative returns. The accompanying table highlights that portfolios with lower Recovery Ratios outperform in terms of cumulative returns, average returns, and Sharpe ratios, while volatility remains relatively stable across all portfolios. However, portfolios with higher Recovery Ratios experience significantly worse maximum drawdowns (max DD) and longer drawdown durations, underscoring the faster recovery and superior performance of portfolios with stricter recovery constraints. Notably, the swift recovery portfolio stands out with considerably higher terminal wealth, despite enduring a large drawdown in early 2020, compared to portfolios with lenient recovery parameters, which struggled to recover and ended the period with losses. This highlights the effectiveness of

Descriptive statistics	Recovery Ratio									
	0.56	0.57	0.58	0.59	0.60	0.61	0.62	0.63	0.64	Unconstrained
Cumulative return (%)	2.30	−27.24	−31.55	−31.92	−31.92	−31.92	−31.92	−31.92	−31.92	−31.92
Average return (%)	0.01	−0.03	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04	−0.04
Min return (%)	−12.72	−12.77	−12.97	−13.11	−13.11	−13.11	−13.11	−13.11	−13.11	−13.11
5th percentile (%)	−1.69	−1.58	−1.67	−1.67	−1.67	−1.67	−1.67	−1.67	−1.67	−1.67
Max return (%)	10.38	10.47	9.95	9.89	9.89	9.89	9.89	9.89	9.89	9.89
Volatility (%)	1.43	1.34	1.32	1.32	1.32	1.32	1.32	1.32	1.32	1.32
Sharpe ratio	0.01	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
Max DD (%)	37.05	38.05	38.17	38.94	38.94	38.94	38.94	38.94	38.94	38.94
Max DD duration (day)	237	608	812	816	816	816	816	816	816	816

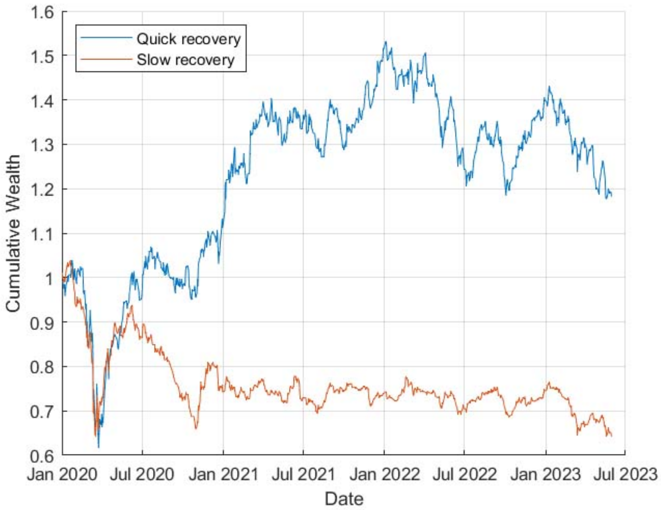
FIGURE 6. (color online) Cumulative wealth indices of efficient portfolios under different recovery constraints. Source: authors' calculation.

rapid recovery strategies, as the quick recovery portfolio's ability to rebound from early losses contributes to its superior ending wealth, making it the only portfolio to remain profitable.

A clear gap is observed when comparing cumulative returns from quick- and slow-recovery portfolios. The quick-recovery portfolio gains around 20% from the initial investment, while the slow-recovery counterpart incurs a loss of about 25%. The quick recovery portfolio's ability to bounce back from initial losses, as evidenced in Figure 7, leads to its higher ending wealth. This aligns with earlier analyses, showing that the portfolio with an average Recovery Ratio of 0.56 remains the only one unscathed at the end of the evaluation period.

An examination of the longest time under water in Figure 7 underscores a distinct pattern: the quick-recovery portfolio experiences a significant shock solely in the initial half of 2020, promptly reversing its trajectory to accumulate positive returns until the conclusion of the evaluation period. Conversely, the slow-recovery portfolio, ensnared in the aftermath of the pandemic shock, endeavors to rebound but proves unsuccessful. This outcome can be primarily attributed to the composition of the stock pool, exclusively comprising stocks lacking the inherent capability for swift recovery.

The analyses on the out-of-sample dataset highlight the heightened resilience of quick-recovery portfolios. Whether composed of both quick and slow recovery stocks or exclusively quick recovery stocks, these portfolios show a remarkable ability to withstand shocks



Descriptive statistics	Recovery group	
	Quick	Slow
Cumulative return (%)	18.16	−35.83
Average return (%)	0.04	−0.04
Min return (%)	−14.71	−12.90
5th percentile (%)	−2.23	−1.64
Max return (%)	11.91	9.24
Volatility (%)	1.74	1.35
Sharpe ratio	0.02	−0.03
Max DD (%)	−38.37	−38.17
Max DD duration (day)	339	811

FIGURE 7. (color online) Cumulative wealth indices of the quick- and slow-recovery portfolios. Source: authors' calculation.

and self-recover post-crisis. This resilience is a key factor in portfolio construction, emphasizing the importance of considering recovery dynamics for resilient investment strategies. These findings contribute significantly to the discourse on portfolio optimization, revealing how recovery characteristics impact portfolio robustness in dynamic financial landscapes.

Recovery Ratio as an optimization objective. In this section, we shift from previous analyses by making the Recovery Ratio the primary optimization objective instead of a constraint. This experimental approach aims to explore how prioritizing recovery time affects portfolios, alongside considering the portfolio's conditional value at risk as a secondary concern.

The efficient frontier resulting from optimizing the Recovery Ratio as the main objective is compared with the frontier from minimizing Conditional Value at Risk (CVaR) in Figure 8. It reveals a clear trend: prioritizing Recovery Ratio leads to higher CVaR. This divergence arises from the intentional emphasis on the portfolio's recovery capacity, relegating the expected shortfall to a secondary consideration and, consequently, inducing a tendency to overlook the impact stemming from tail losses.

Crucially, under the objective of minimizing CVaR, the risk of optimal portfolios does not necessarily align with their Recovery Ratios. Portfolios characterized by higher CVaR do not inherently exhibit commensurately higher Recovery Ratios, providing evidence that

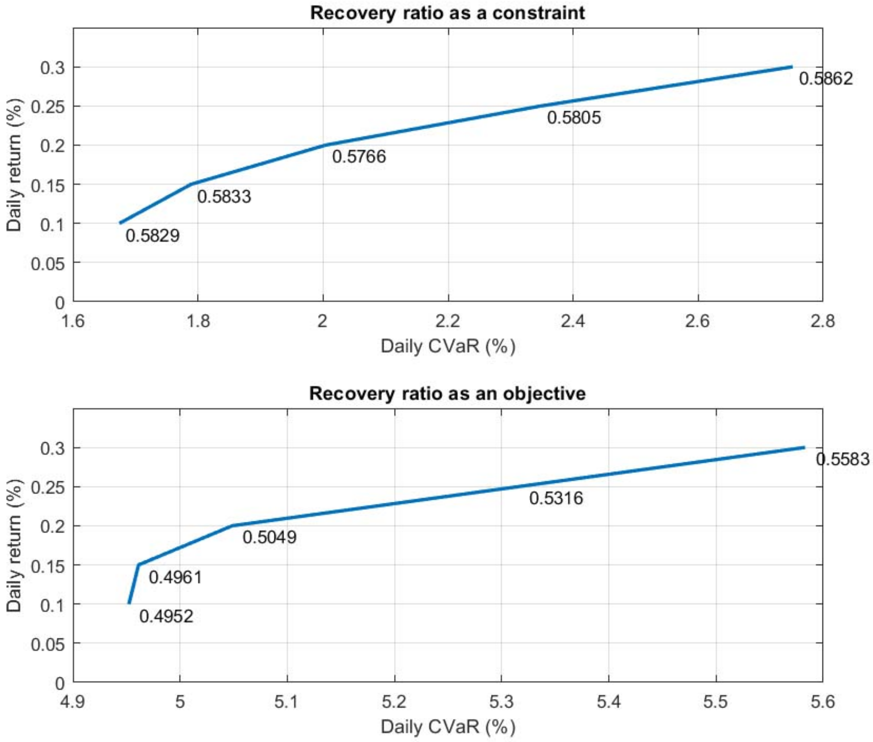


FIGURE 8. An efficient frontier when the Recovery Ratio is constrained to be under 0.6 (upper panel) and when the Recovery Ratio is an optimization objective (lower panel). Source: authors' calculation.

the intensity of extreme losses operates independently of recovery time. Within the frontier that minimizes the Recovery Ratio, marginal disparities in portfolio Recovery Ratios are not markedly pronounced. This observation reflects the dataset's inherent characteristic, where the Recovery Ratios of individual stocks lack conspicuous distinctiveness. Moreover, the portfolio performances demonstrate a notable congruence with those subject to the same Recovery Ratio constraint. This consistent alignment underscores the reliability and stability of portfolio outcomes when employing different methodological approaches to recovery optimization.

To evaluate performance, we conducted a forward test on portfolios, including five derived from cases where the Recovery Ratio is used as a constraint and five where it is employed as an optimization objective, as depicted along the frontiers in Figure 8. The descriptive statistics are summarized in Table 2. Notably, the performance of portfolios under Recovery Ratio constraints aligns closely with the results shown in Figure 8. The statistics reveal that minimizing the Recovery Ratio provides an improvement in performance compared to the cases where the Recovery Ratio constraint exceeds 0.6. Nonetheless, the cumulative return remains negative, unlike portfolios with a tight Recovery Ratio constraint of 0.56 which achieved a cumulative return of 2.3% as exhibited in Figure 8. This analysis thus underscores that minimizing downside losses, combined with a stringent Recovery Ratio constraint, yields the best performance, as such portfolios effectively mitigate both large and prolonged losses.

5. **Summary.** This study embarks on a sophisticated exploration of portfolio optimization, delving into the intricate dynamics of recovery and its influence on risk-return profiles. At its core lies the novel metric – the Recovery Ratio – a distinctive tool developed

TABLE 2. (color online) The descriptive statistics are averaged across the resulting portfolios where the Recovery Ratio is employed as both an objective and a constraint during the out-of-sample period. Each statistic represents the mean of five portfolios along the frontier depicted in Figure 8.

Descriptive statistics	Recovery Ratio is used as	
	Objective	Constraint
Cumulative return (%)	−21.80	−31.92
Average return (%)	−0.01	−0.04
Min return (%)	−12.94	−13.11
5th percentile (%)	−1.64	−1.67
Max return (%)	13.26	9.89
Volatility (%)	2.08	1.32
Sharpe ratio	0.00	−0.03
Max DD (%)	37.22	38.94
Max DD duration (day)	816	816

to quantify the speed and efficiency with which portfolios bounce back from downturns. The narrative unfolds across multiple dimensions, examining the significance of time under water, the conceptualization of the Recovery Ratio, its integration into portfolio optimization, and the significant implications for portfolio performance.

The foundation of this exploration rests on the recognition of the critical role played by managing time under water in stock portfolios. Introducing the Recovery Ratio as a novel metric of rebound efficiency, this analysis brings to light a crucial yet often overlooked factor in conventional risk assessments. The Recovery Ratio, derived as the recovery period divided by time under water, introduces a deeper dimension to our understanding of portfolio resilience. The analysis expands to the practical application of Recovery Ratios in constructing portfolios. Drawing from empirical evidence grounded in historical stock returns of SET50, the research accentuates the potential advantages conferred by the inclusion of quick-recovery stocks, particularly during market downturns.

The study proposes the Recovery Ratio both as an objective function and a constraint in portfolio optimization. This integration into optimization problems is examined thereafter, unraveling distinctions when the Recovery Ratio assumes a central role in the optimization process. The findings shed light on the trade-offs between recovery dynamics and risk considerations, significantly impacting risk profiles and allocation strategies. Integral to the overarching narrative is a key empirical finding that weaves through the research: quick-recovery portfolios, while appearing inferior in terms of risk-return efficiency when observed through the lens of efficient frontiers, remarkably outperform slow-recovery portfolios in backtests and forward tests. This paradox underscores a critical consideration – that conventional risk measures such as CVaR, fixated on minimizing losses, might overlook practical properties such as loss recovery, which is crucial for portfolio performance in dynamic market conditions.

While the study delivers meaningful insights, certain aspects present opportunities for further exploration. The analysis, based on the SET50 index, provides a deep understanding of a representative and influential market, but future research could extend the methodology to less volatile or structurally different markets to assess generalizability. The results, although supported by a robust dataset and methodology, could also benefit from expanded robustness tests, such as sensitivity analyses or validation across alternative datasets. Lastly, the unavailability of drawdown duration metrics in negative territory during the out-of-sample period suggests an avenue for refining methods to evaluate recovery dynamics under sustained downturns. These considerations do not detract from the study's contributions but highlight promising directions for future research to build on its findings.

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