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Enhanced Index-Tracking Strategies Based on Systemic Financial Shocks: A Comparison of Countries Versus Sectors Investments

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Abstract: Since the launch of the first replicating funds in the 1970s, index-linked strategies have captured the interest of equity investors. On the one hand, active investing does not generally lead to higher risk-adjusted returns than a passive approach. On the other hand, passive vehicles cannot optimize the risk exposure to the equity markets without introducing elements of active management. The enhanced index-tracking offers all the advantages of traditional passive investing but aims to generate better returns than the reference benchmark. However, in the last decades, the financial system integration increased, reducing the diversification opportunities across markets, and meanwhile, more and more frequent extreme events affected the world. This amplified systemic instability caused unsatisfactory results even for these investment strategies. To better manage the markets turmoil and reduce losses, we propose alternative portfolio designs to improve the traditional index-tracking techniques. We include the systemic risks directly into the enhanced indexation problem and impose a minimum guaranteed extra-return on the benchmark with turnover control. The analysis builds on country and industry allocation policies in selected European markets from January 2004 to October 2021. Our findings prove that the proposed strategies generate consistent excess returns over the benchmark and outperform other indexing strategies and the equally weighted and risk parity portfolios.

Keywords: Enhanced Index Tracking, Downside Risk, Systemic Risks, European Market, Sector VS Country Allocation

1. Introduction

Index-linked investing is one of the most widely used vehicles for equity investors and is likely to continue to be so because of the increasing number of accessible funds [1].

An index-tracking strategy does not involve any market views outside the set of rules of the index. The only objective is to deliver the benchmark returns. Unlike active management, no stock picking is involved in index management. However, a tracking portfolio that just buys all the constituents to replicate the index is likely to underperform its benchmark because of the high rebalancing costs.

The evolving landscape of financial markets has led in the past years to a ramp-up stage to develop a new range of index-linked investment strategies to overcome this pitfall. On the one hand, the so-called partial tracking strategy achieves the replication of the index by investing in a limited number of stocks and minimizing the tracking error between the return of the tracking portfolio and that of the index [2-4]. On the other hand, enhanced index-tracking strategies aim to generate moderate and consistent excess returns with respect to the tracked index by minimizing a function of the tracking error and, at the same time, maximizing the excess return of the portfolio [5-8].

Nowadays, investors operate in a globally integrated financial system characterized by marked instability, due to more and more frequent extreme events like the 2008-9 subprime crisis, the 2015 U.S. economic slow-down, the 2016

Chinese stock market crash, and the recent Coronavirus disease (COVID-19) pandemic crisis. As a consequence, the returns on international equities tend increasingly to move jointly across countries, leading to the so-called systemic risk. Thus, it is fundamental to evaluate the effects of these events on index-linked portfolios.

Many studies focus the analysis on a portfolio of stocks issued by listed financial firms and their interconnection to measure financial institutions' systemic risk contribution [9-13]. But only a limited number of authors focus their attention on market indexes and analyze the implications of systemic risk on the construction of portfolios of investments [14-18].

Our contribution is the introduction of two new index-linked strategies properly devised to reduce the exposition to market downturn while tracking the index. Both have to minimize the tracking error at the tail level with a minimum guaranteed extra-return on the benchmark. To avoid the risk of under diversification, we introduce a constraint regarding the minimum and maximum amount of capital to invest in each asset. Further, to reduce the rebalancing costs, we introduce a turnover limit. The difference between these two approaches regards how we define the idiosyncratic shocks affecting the excess returns to the benchmark. For the first strategy, it suffices that a restricted number of stocks in the market shows high idiosyncratic risk. The second identified a systemic event with an extreme loss of the benchmark.

Our models differ from those presented in the literature for the following aspects. In our first allocation model, we relax the assumption in [17] that all assets have to co-move in the tail in order to identify an extreme event, allowing the investor to fix the extreme event severity. Our second model uses the same definition for systemic event as [16], but differs in considering the distribution of excess returns to the benchmark instead of the returns. In addition, our investment strategies include a limit on the concentration of assets that cannot be found in [16] and [17]. Summing up, our portfolio designs are more flexible and better adapted to investors' behaviour.

Then, we calibrate the proposed index-linked portfolios to the European equity index and examine whether country diversification provides benefits over sector diversification. We also investigate the profitability of the proposed enhanced index tracking models compared to various weighting and optimization approaches, such as equally weighted, risk parity, index-tracking, downside index-tracking, mean-CVaR.

The empirical results, based on 13 European stock indices and 11 sector groups from January 1999 to October 2021, show that considering systemic shocks in the development of index-linked strategies improves the out-of-sample performance. Indeed, our portfolios beat the benchmark and other index-linked approaches consistently, so as the equally weighted and risk parity schemes in terms of ex-post performance ratios and net wealth, both at country and sector level. According to Ehling P et al. [19], the country-based portfolio with diversification constraints is better in most periods [19]. However, the sector-based portfolio performs better during the financial system crisis. An explanation for this behaviour is that the sector-based portfolio permits a higher diversification but faces higher rebalancing costs; the country-based portfolio presents a lower diversification because of the higher assets correlations but requires lower rebalancing costs.

The structure of the paper is as follows. In the next section, we present the theoretical framework. In particular, we introduce different definitions of a systemic financial event and define the index-linked portfolio optimization problem. Then, we describe the ex-post criteria used to evaluate these strategies compared to a set of commonly used investment rule-based weighting schemes. Section 3 includes the description of the employed datasets and explores the main results of the empirical analysis. Finally, some concluding remarks and ideas for future research are drawn in Section 4.

2. Models and Methodologies

2.1. Investment Framework

Let us consider a financial market with n risky assets and represent a portfolio by the vector of assets weights $w = (w_1, \ldots, w_n)^T$. If $P_{i,t}$ is the price of asset i at time t, then its rate of return at time t is given by $R_{i,t} = P_{i,t}/P_{i,t-1} - 1$ while its log-return at time t is defined as $r_{i,t} = \log(P_{i,t}/P_{i,t-1})$, with $i = 1,\ldots, n$. Similarly, if we denote by $P_{b,t}$ the price of the market index at time t, the corresponding rate of return and log-return are respectively $R_{b,t} = P_{b,t}/P_{b,t-1} - 1$ and $r_{b,t} = \log(P_{b,t}/P_{b,t-1})$. The portfolio rate of return at time t is $R_{p,t}(w) = \sum_{i=1}^{n} w_i R_{i,t} = w^T R_t$, with $R_t = (R_{1,t}, \ldots, R_{n,t})^T$. Notice that we will skip the dependence of R_i and R_b on t and of R_p on w and t where it will b:e clear from the context. Accordingly, we denote by $R_p - R_b$ the excess portfolio return over the benchmark.

2.1.1. Tracking Measures Based on Systemic Events

A function of $R_p - R_b$ measures the tracking accuracy of a portfolio w to the benchmark.

An example of that function is the so-called tracking error variance, defined as the variance of the extra returns of the tracking portfolio [20]. Even if its interpretation is intuitive (lesser values indicate better fits), we cannot directly employ it as a tracking measure because variance may not necessarily represent the movements of the benchmark, as when the extra returns are constant.

Reference [3] provides a solution to this pitfall, defining the tracking error as:

$$TE(w) = E\left(\left|R_p - R_b\right|^{\alpha}\right)^{1/\alpha} \tag{1}$$

where $\alpha > 0$ is the power by which portfolio excess returns are penalized. In general, the choice $\alpha = 2$ guarantees good performances [21].

If the investor is interested in evaluating the tracking portfolio when it underperforms the index, she can measure the downside risk of the portfolio excess returns as in Kaucic M et al. [8]:

$$TE^{-}(w) = E\left(\left(R_p - R_b\right)^2 | R_p - R_b < 0\right)^{1/2} \quad (2)$$

In this paper, we analyze the benefits of considering tracking measures based on the tail behaviour of the portfolio excess return distribution.

On the one hand, to properly evaluate the tracking capabilities in case of extreme losses to the benchmark, a more accurate measure with respect to (2) could be the so-called conditional value-at-risk of the portfolio excess returns at the confidence level α [22]:

$$CVaR_\alpha(w) = -E(R_p - R_b | R_p - R_b \leq -VaR_\alpha(R_p - R_b)) \quad (3)$$

where $VaR_\alpha(Y) = -\inf\{y | P(Y \leq y) > \alpha\}$ is the value-at-risk of the random variable Y at the confidence level $\alpha \in (0,1)$.

$CVaR_\alpha$ represents the portfolio expected extra return for extra returns below the level $VaR_\alpha(R_p - R_b)$.

On the other hand, to estimate the impact of the financial system instability on the tracking portfolio, we consider two different definitions of the idiosyncratic shocks, corresponding to two alternative tracking measures.

Based on the idea of assets co-movement introduced in Biglova A et al. [17], we say that a systemic downward trend happens when at least a predefined percentage δ of the assets jointly move below their value-at-risk levels. The set of these systemic events can be written as:

$$SE_\alpha^\delta = \left\{\omega | \textstyle\sum_{i=1}^{n} I_{\{R_i \leq -VaR_\alpha(R_i)\}}(\omega) \geq \delta n\right\} \quad (4)$$

where $VaR_\alpha(R_i)$ represents the extreme loss associated with asset i, for $i = 1, \ldots, n$.

The value of δ allows the investor to fix the level of severity in defining the extreme event. The higher the value of δ, the more assets are required to be in distress.

If SE_α^δ in (4) is not empty, we define the following tracking measure:

$$CoETL_\alpha^\delta(w) = -E(R_p - R_b | SE_\alpha^\delta) \quad (5)$$

which represents the expected value of the portfolio extra returns when a percentage δ of the assets has a consistent loss. We call this measure generalized co-Expected Tail Loss, as it can be noticed that when δ=100%, $CoETL_\alpha^\delta$ reduces to the $CoETL_\alpha$ measure proposed in Biglova A et al. [17].[1]

We now identify a systemic event with an extreme loss of the benchmark. The resulting set of the idiosyncratic shocks is

$$SE_\alpha^b = \left\{\omega | I_{\{R_b \leq -VaR_\alpha(R_b)\}}(\omega) = 1\right\} \quad (6)$$

Then, the associated tracking measure is:

$$C_bVaR_\alpha(w) = -E(R_p - R_b | SE_\alpha^b) \quad (7)$$

where the expectation of the portfolio extra returns is evaluated considering the excess returns realized when the benchmark falls below its VaR at the confidence level α.

2.1.2. Portfolio Constraints

The proposed portfolio designs include the following set of real-world constraints.

We require that the capital invested is equal to the capital available at time T. In terms of portfolio weights, this is equivalent to impose

$$\textstyle\sum_{i=1}^{n} w_i = 1 \quad (8)$$

To avoid extreme positions and favour diversification, we impose minimum and maximum limits for the weights of the stocks in the portfolio. Let us denote by l_i and u_i the lower bound and the upper bound for the weight w_i of stock i then

$$l_i \leq w_i \leq u_i, i = 1, \ldots, n \quad (9)$$

with $0 \leq l_i < u_i \leq 1$. Note that leverage is not allowed in this study.

We propose portfolio allocation models with a minimum guaranteed expected extra return $\varepsilon \geq 0$. This condition can be written as follows

$$E\left(R_p - R_b\right) \geq \varepsilon \quad (10)$$

Further, to get an impression of the transaction costs incurred at a given rebalancing time t, we also consider the so-called portfolio turnover, which is defined as the sum of the absolute values of the rebalancing trades across all the assets at time t [23]. The corresponding constraint is

$$\textstyle\sum_{i=1}^{n} \left|w_{i,t} - w_{i,t-}\right| \leq TR \quad (11)$$

where $w_{i,t}$ is the portfolio weight of asset i at time t, $w_{i,t-}$ is the portfolio weight of asset i before rebalancing, and TR in [0, 1] is the maximum turnover rate. If TR is set to 0, rebalancing is not allowed. As TR increases, the allowed costs for the new portfolio increase.

Summing up, we say that a portfolio is admissible or feasible if it satisfies (8), (9), (10) and (11). The set of all admissible portfolios is denoted with W.

2.2. Optimization Process

Following Farinelli S et al., we structure our optimization process as a multi-period asset allocation plan [24]. We divide the investment horizon $[0, T]$ into T months, and the weights for each portfolio are determined at the last trading day of each month, based on simulated future scenarios.

More specifically, let us introduce a probability space $(\Omega, \mathcal{F}, P)$ to model the future values of the assets and assume that the random variables R_p and R_b are p-integrable. For each tracking measure ρ presented in Section 2.1.1 and each monthly unit period $[t-1, t)$, $t=1,\ldots, T$, we invest all wealth in the risky portfolio that solves the following optimization problem:

$$\min_{w \in W} \rho(w) \quad (12)$$

1 Indeed, the conditional event can be written as $SE_\alpha^1 = \left\{\omega | \sum_{i=1}^{n} I_{\{R_i \leq -VaR_\alpha(R_i)\}}(\omega) = n\right\} = \left\{\omega | \prod_{i=1}^{n} I_{\{R_i \leq -VaR_\alpha(R_i)\}}(\omega) = 1\right\} = \left\{\omega | I_{\cap_{i=1}^{n}\{R_i \leq -VaR_\alpha(R_i)\}}(\omega) = 1\right\}$

Thus, the tracking measure becomes $CoETL_\alpha^1(w) = -E(R_p - R_b | SE_\alpha^1) = -E\left(R_p - R_b \middle| R_1 \leq -VaR_\alpha(R_1), \ldots, R_n \leq -VaR_\alpha(R_n)\right) = CoETL_\alpha(w)$

A scenario consists of n+1 return realizations in this setting, one for each asset, including the benchmark. We will refer to the *t*–th realization of the rate of return of asset i as its realization under scenario *t*. First, we simulate the empirical distribution of the monthly portfolio excess returns R_p - R_b using *S* scenarios based on daily historical data. Then, we calculate the portfolio expected excess return and the value of the risk measure ρ.

Let us denote the number of trading days in the period *[t-1, t)* by D_t and the number of trading days in the in-sample window by *M*. We consider a data set of $(M + \sum_t D_t) \times (n+1)$ historical prices for the *n* assets plus the benchmark and adopt a rolling time window procedure to rebalance optimal portfolios. We solve the optimization problem (12) for overlapping windows of length *M* built by moving forward with step size D_t. We update the in-sample window by removing the oldest data and including the most recent information. This procedure is repeated *T* times until the last available observation.

We generate the monthly scenarios through the filtered historical bootstrap approach [25, 26]. The choice of this method is justified by its forecasting adequacy in risk management (see, for instance, [27] and the references therein). We implement the following steps for each unit period *[t-1, t)*.

We use the *M* daily prices of the *t*–th in-sample window to fit a univariate Student–*t* ARMA(1,1)–EGARCH(1,1) model to each log-return series in the data set as follows:

$$\begin{gathered} r_{j,s} = a_j + b_j r_{j,s-1} + c_j \varepsilon_{j,s-1} + \varepsilon_{j,s} \\ \varepsilon_{j,s} = \sigma_{j,s} u_{j,s} \\ \log \sigma_{j,s}^2 = \delta_j + \beta_j \log \sigma_{j,s-1}^2 + \alpha_j \left(|u_{j,s-1}| - E(|u_{j,s-1}|) \right) + \gamma_j u_{j,s-1} \end{gathered} \tag{13}$$

where $j = 1,...,n+1$, $s=1,...,M$, and $u_{j,s}$ follows a Student-*t* distribution with v_j degrees of freedom.

The vector $\widehat{\theta}_j = (\hat{a}_j, \hat{b}_j, \hat{c}_j, \hat{\delta}_j, \hat{\beta}_j, \hat{\alpha}_j, \hat{\gamma}_j, \hat{v}_j)$ represents the maximum likelihood estimates for the parameters associated with the *j*–th time series. In this manner, we remove autocorrelation and heteroscedasticity from the data.

1. For each log-return series *j*, we compute the standardized innovations $\hat{u}_{j,s} = \hat{\varepsilon}_{j,s}/\hat{\sigma}_{j,s}$ using the estimates in $\widehat{\theta}_j$. Then, we define the matrix $\widehat{U} = (\hat{u}_{j,s})^T$.
2. Notice that $\hat{\varepsilon}_{j,s}$ and $\hat{\sigma}_{j,s}$ are the *s*–th empirical residual and the estimated volatility of asset *j*, for $s = 1, \dots, M$.
3. We randomly sample with replacement D_t rows from $\widehat{U}$ to form the $D_t \times (n+1)$ matrix $U^* = (u_{i,s}^*)$. Thus, cross-sectional correlations and multivariate shocks of the system are implicitly captured.
4. We set $\sigma_{j,0}^* = \hat{\sigma}_{j,M}$ and $\varepsilon_{j,0}^* = \hat{\varepsilon}_{j,M}$ and simulate at *t-1* the log-returns $r_{j,s'}^*$ of asset *j* for the next D_t days using the following recursive scheme:

$$\begin{gathered} \log \sigma_{j,s'}^{*2} = \hat{\delta}_j + \hat{\beta}_j \log \sigma_{j,s'-1}^{*2} + \hat{\alpha}_j \left(|u_{j,s'-1}^*| - E(|u_{j,s'-1}^*|) \right) + \hat{\gamma}_j u_{j,s'-1}^* \\ \varepsilon_{j,s'}^* = \sigma_{j,s'}^* u_{j,s'}^* \\ r_{j,s'}^* = \hat{a}_j + \hat{b}_j r_{j,s'-1}^* + \hat{c}_j \varepsilon_{j,s'-1}^* + \varepsilon_{j,s'}^* \end{gathered} \tag{14}$$

for $j = 1, \dots, n+1$ and $s' = 1, \dots, D_t$.

5. The simulated monthly rate of return of asset *j* for month *t*, denoted by $R_{j,t}^*$, is then given by

$$R_{j,t}^* = exp\{\textstyle\sum_{s'=1}^{D_t} r_{j,s'}^*\} - 1 \tag{15}$$

for $j = 1, \dots, n+1$ and $t = 1, \dots, T$.

Notice that the vector $R_t^* = (R_{1,t}^*, \dots, R_{n,t}^*)^T$ represents the realization of R_t under scenario *t*. Similarly, $R_{b,t}^* = R_{n+1,t}^*$ is the realization of $R_{b,t}$ under the same scenario.

By repeating steps 3–5, we obtain *S* scenarios with the corresponding realizations for R_t and $R_{b,t}$. Finally, we get the empirical distribution of the monthly portfolio excess returns $w'R_t - R_{b,t}$ for month *t* as follows:

$$\hat{F}(x; w) = \frac{1}{S} \textstyle\sum_{\tau=1}^{S} I_{\{Y(\tau;w) \le x\}} \tag{16}$$

where $Y(\tau;w) = w_1 R_{1,\tau}^* + \dots + w_n R_{n,\tau}^* - R_{b,\tau}^*$ is the portfolio excess return under scenario τ.

We remark that in problem (11) the vector of portfolio weights *w* is unknown at time *t–1*, but we will use $\hat{F}(x; w)$ to calculate at time *t* portfolio expected excess return and the value of the risk measure ρ.

2.3. Performance Measures

We evaluate the attractiveness of the investment opportunities in terms of risk-adjusted performance measures. Let us indicate by r_t^{out}, $t = 1, \dots, T$, the portfolio rates of return for each strategy in the out-of-sample period *[0, T]*. The first performance measure we introduce is the out-of-sample Sharpe ratio (*SR*) [28], which evaluates the compensation earned per unit of portfolio total risk. It is defined as the ratio between the annualized average μ^{out} of r_t^{out} and the annualized sample standard deviation σ^{out}, that is

$$SR = \frac{\mu^{out}}{\sigma^{out}} \tag{17}$$

The second measure we consider is the so-called Omega ratio (*Omega*) [29], defined as the ratio of gains to losses at a minimum acceptable level of expected return. In this paper, we set this threshold to zero, and the resulting performance ratio becomes the following:

$$Omega = \frac{\sum_{t=1}^{T} r_t^{out} 1_{\{r_t^{out} > 0\}}}{-\sum_{t=1}^{T} r_t^{out} 1_{\{r_t^{out} < 0\}}} \tag{18}$$

In general, the out-of-sample Sharpe ratio is more focused on the central part of the portfolio return distribution. In contrast, the Omega ratio considers all information about risk and return because it depends on the total return distribution.

For each strategy, we also compute its wealth at day t as:

$$W_t = W_{t-1}\left(1 + R_{p,t}\right) - c_t(w_{t-1}, w_t) \qquad (19)$$

where c_t is the transaction cost function that depends on the current and previous portfolios, denoted by w_t and w_{t-1}, respectively. Then, we compare the profitability of the investments using the so-called compound annual growth rate (*CAGR*) [30], which is calculated as

$$CAGR = \left(\frac{W_T}{W_0}\right)^{12/T} - 1 \qquad (20)$$

where T is the number of months in the out-of-sample period, W_0 represents the initial wealth, and W_T is the final wealth.

We consider the maximum drawdown (*MDD*) to quantify the downside risk of the distribution of the out-of-sample portfolio returns. It represents the maximum loss incurred from a peak to a trough before a new peak is attained.

To provide further information about the left tail of the ex-post portfolio return distribution, we also calculate the conditional value-at-risk (*CVaR*). After sorting out-of-sample portfolio returns in ascending order, that is $r_{(1)}^{out} \leq r_{(2)}^{out} \leq \ldots \leq r_{(T)}^{out}$, we first identify the ex-post value-at-risk at the level confidence α, which is defined as

$$VaR_\alpha = -r^{out}_{(\lfloor \alpha T)\rfloor+1)} \qquad (21)$$

where $\lfloor \cdot \rfloor$ is the floor function.

The ex-post conditional value-at-risk is then given by:

$$CVaR_\alpha = -\frac{1}{\lfloor \alpha T)\rfloor+1} \sum_{t=1}^{\lfloor \alpha T)\rfloor+1} r^{out}_{(t)} \qquad (22)$$

In the experimental comparisons, we will set $\alpha = 10\%$.

The average on all rebalancing times of the normalized diversification index (*DI*) [31] is used to measure the diversification level of the optimal portfolios. It is given by

$$\mathrm{DI} = \frac{1}{T}\sum_{t=1}^{T} \frac{1-\sum_{i=1}^{n}\left(w_{i,t}\right)^2}{1-\frac{1}{n}} \qquad (23)$$

The term in the outer summation is 0 when all the capital is concentrated in one single asset and is 1 for the equal-weighted portfolio. Thus, the highest diversified portfolio presents the highest *DI* value.

Finally, to get an impression of the transaction costs involved, we calculate the average turnover over the out-of-sample period *TO* as defined in [32]:

$$TO = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n}\left|w_{i,t} - w_{i,t-}\right| \qquad (24)$$

where T is the number of rebalances realized. A greater value of *TO* indicates a more expensive investment strategy.

2.4. Rule-based Weighting Methods

In the ex-post analysis, we compare the asset allocation models' performance with those of two prominent weighting methods, namely the equally weighted and the risk parity.

The first portfolio construction assigns equal weights to every asset, that is $w_i = 1/n$ for $i = 1, \ldots, n$.

Each portfolio component contributes equally to portfolio risk in the risk parity construction, neglecting correlations between asset returns. Therefore, the weighting scheme is

$$w_i = \frac{1/\hat{\sigma}_i^2}{\sum_{j=1}^{n} 1/\hat{\sigma}_j^2} \qquad (25)$$

where $\hat{\sigma}_i^2$ is the estimate of the variance of asset return i, for $i = 1, \ldots, n$.

As for all other strategies, we rebalance both portfolios monthly.

3. Empirical Analysis

3.1. Data Description

We consider the problem of optimizing equity-only portfolios, where the allocation policies are given at the country and sector level. The MSCI Europe stock index (thereafter EMU index) is employed as the benchmark and permits calculating extra returns. Based on the segmentation policies, we consider the following two datasets of daily closing prices of indices:

a) *Countries,* collecting 12 stock indices by MSCI (Switzerland, France, Germany, Italy, Spain, Finland, the Netherlands, Denmark, Norway, Sweden, Poland, and the European Emerging Countries index (thereafter EEC index)), and the FTSE100 stock index for the United Kingdom.
b) *Sectors,* including 11 European sector groups based on the Global Industry Classification Standard (Financials, Industrials, Health Care, Energy, Communication Services, Utilities, Materials, Consumer Staples, Consumer Discretionary, Information Technology, and Real Estate).

The EMU index and the other 24 total return indices are downloaded from Datastream for the most extended jointly available period from 01/01/1999 to 29/10/2021, corresponding to 5956 observations. In the experiments, each in-sample window involves 1251 trading days, which correspond approximately to five years. The rebalancing takes place monthly (almost 21 observations each month). The out-of-sample evaluation period ranges from 01/01/2004 to 29/10/2021 and includes 214 months.

Tables 1-3 show the descriptive statistics with monthly frequency for the EMU index, countries and sectors indices.

The mean country stock returns range from 0.3% (Italy) to 1.1% (Denmark), which is slightly higher than the lowest and higher than the highest monthly mean return of the sector indices with a minimum of 0.2% (Communication Services) and a maximum of 0.9% (Materials), respectively.

The group of country indices presents, on average, a slightly higher monthly mean return than that of the sector indices, namely 0.7% for the former and 0.6% for the latter. Both are higher than the monthly mean return of the EMU index (0.5%).

In terms of volatility, the average standard deviation for the sector indices (5.5%) is slightly lower than that of the country indices (6%). Both groups have the same minimum standard deviation (3.7% for Switzerland and the Health Care sector) and very similar maximum standard deviations (8.4% for Poland and 8.2% for the Information Technology sector). The two asset classes are riskier than the benchmark, which has a volatility of 4.5%.

Based on the values of skewness, kurtosis, and the Jarque-Bera statistic, we reject the hypothesis of normally distributed stock returns for the EMU index and all 24 indices.

Tables 3-4 display the correlation structure among country indices and sector indices, respectively. Consistent with the literature [33, 34], we observe the highest correlations between the pairs of direct neighbouring countries, as Germany and France (0.917), Netherlands and France (0.892), Italy and France (0.871). In contrast, we measure the lowest correlation for country-pairs Switzerland and Finland (0.495) and Switzerland and the EEC index (0.492). Overall, the results for country indices are higher (average correlation of 0.677) than for sectors (average correlation of 0.545). We observe the lowest correlation between Communication Services and Real Estate (0.331) for the sector indices and the highest between Consumer Discretionary and Industrials (0.905).

In summary, our descriptive data analysis indicates that while the group of country indices provide higher mean returns, the sector indices are less volatile. Further, the correlation structure of the sectors indices suggests that an optimization across this asset class should provide higher diversification benefits than a country-based portfolio allocation.

Table 1. *Summary statistics of the European market index.*

	EMU Index
Min	-0.143
Max	0.144
Mean	0.005
Std Dev	0.044
Skew	-0.495
Kurt	4.253
JB	28.997
p-value	0.001

* In this and the following tables, Min = Minimum; Max = Maximum; Std Dev = Standard deviation; Skew = Skewness; Kurt = Kurtosis; JB = Jarque-Bera.

Table 2. *Descriptive statistics of the country indices.*

	UK	CH	F	D	I	E	FIN	NL	DK	N	S	PL	EEC
Min	-0.159	-0.118	-0.176	-0.249	-0.224	-0.220	-0.310	-0.184	-0.177	-0.269	-0.191	-0.267	-0.280
Max	0.133	0.103	0.197	0.209	0.235	0.261	0.329	0.132	0.186	0.183	0.257	0.272	0.236
Mean	0.004	0.006	0.006	0.006	0.003	0.005	0.007	0.007	0.011	0.009	0.009	0.007	0.009
Std Dev	0.042	0.037	0.050	0.059	0.058	0.059	0.081	0.051	0.050	0.066	0.066	0.084	0.074
Skew	-0.528	-0.532	-0.358	-0.452	-0.128	-0.004	0.246	-0.780	-0.445	-0.713	0.014	0.066	-0.360
Kurt	4.063	3.464	4.462	5.068	4.615	5.174	6.266	4.578	4.493	5.047	4.975	3.911	4.270
JB	25.526	15.327	30.125	57.968	30.410	53.740	124.108	56.007	34.351	70.796	44.366	9.642	24.252
p-value	0.001	0.005	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.016	0.001

* The columns report the statistics for the United Kingdom (UK), Switzerland (CH), France (F), Germany (D), Italy (I), Spain (E), Finland (FIN), the Netherlands (NL), Denmark (DK), Norway (N), Sweden (S), Poland (PL), and the European Emerging Countries (EEC).

Table 3. *Descriptive statistics of the sector indices.*

	FIN	IND	HEA	ENE	COMM	UTIL	MAT	C_ST	C_DIS	IT	R_EST
Min	-0.242	-0.217	-0.103	-0.153	-0.219	-0.165	-0.252	-0.117	-0.216	-0.275	-0.229
Max	0.325	0.206	0.114	0.338	0.222	0.123	0.210	0.126	0.195	0.384	0.190
Mean	0.004	0.008	0.006	0.006	0.002	0.006	0.009	0.007	0.007	0.007	0.006
Std Dev	0.065	0.056	0.037	0.059	0.058	0.043	0.060	0.035	0.056	0.082	0.053
Skew	-0.110	-0.790	-0.118	0.637	-0.008	-0.420	-0.464	-0.439	-0.328	0.234	-0.506
Kurt	6.755	5.465	3.090	6.794	5.892	3.871	4.659	3.942	4.544	5.908	5.708
JB	160.916	97.526	0.721	182.239	95.124	16.658	41.112	18.873	32.009	98.692	95.081
p-value	0.001	0.001	0.500	0.001	0.001	0.004	0.001	0.003	0.001	0.001	0.001

* The columns report the statistics for the Financials (FIN), Industrials (IND), Health Care (HEA), Energy (ENE), Communication Services (COMM), Utilities (UTIL), Materials (MAT), Consumer Staples (C_ST), Consumer Discretionary (C_DIS), Information Technology (IT), and Real Estate (R_EST).

Table 4. *Correlation matrix of the country indices.*

	UK	CH	F	D	I	E	FIN	NL	DK	N	S	PL	EEC
UK	1.000												
CH	0.729	1.000											
F.	0.836	0.731	1.000										
D	0.784	0.713	0.917	1.000									
I.	0.719	0.594	0.871	0.793	1.000								
E	0.693	0.549	0.832	0.760	0.840	1.000							
FIN	0.607	0.495	0.701	0.657	0.584	0.524	1.000						

	UK	CH	F	D	I	E	FIN	NL	DK	N	S	PL	EEC
NL	0.816	0.761	0.892	0.858	0.777	0.736	0.608	1.000					
DK	0.670	0.638	0.684	0.686	0.580	0.541	0.525	0.731	1.000				
N	0.779	0.566	0.750	0.700	0.666	0.608	0.504	0.739	0.665	1.000			
St.	0.735	0.637	0.831	0.839	0.697	0.679	0.698	0.790	0.706	0.675	1.000		
PL	0.559	0.501	0.660	0.655	0.586	0.629	0.544	0.602	0.510	0.564	0.622	1.000	
EEC	0.700	0.492	0.691	0.679	0.632	0.618	0.573	0.633	0.555	0.708	0.661	0.713	1.000

* The columns report the statistics for the United Kingdom (UK), Switzerland (CH), France (F), Germany (D), Italy (I), Spain (E), Finland (FIN), the Netherlands (NL), Denmark (DK), Norway (N), Sweden (S), Poland (PL), and the European Emerging Countries (EM).

Table 5. *Correlation matrix of the sector indices.*

	FIN	IND	HEA	ENE	COMM	UTIL	MAT	C ST	C DIS	IT	R EST
FIN	1.000										
INDS	0.833	1.000									
HEA	0.422	0.4102	1.000								
ENE	0.564	0.5518	0.339	1.000							
COMM	0.519	0.5849	0.273	0.338	1.000						
UTIL	0.636	0.6277	0.464	0.452	0.473	1.000					
MAT	0.742	0.8424	0.364	0.625	0.424	0.541	1.000				
C ST.	0.490	0.5733	0.674	0.414	0.312	0.587	0.499	1.000			
C DIS	0.805	0.9052	0.410	0.508	0.601	0.554	0.779	0.556	1.000		
IT	0.642	0.7745	0.350	0.367	0.692	0.462	0.596	0.365	0.767	1.000	
R EST	0.673	0.6324	0.442	0.418	0.331	0.612	0.578	0.574	0.616	0.396	1.000

* The columns report the statistics for the Financials (FIN), Industrials (IND), Health Care (HEA), Energy (ENE), Communication Services (COMM), Utilities (UTIL), Materials (MAT), Consumer Staples (C_ST), Consumer Discretionary (C_DIS), Information Technology (IT), and Real Estate (R_EST).

3.2. Portfolios Settings

The buy-in thresholds in (8) are $l_i = 0$ and $u_i = 0.20$ for each asset *i,* as in Bessler W et al [34].

Based on a preliminary analysis of costs and benefits, the turnover rate in (9) is set to 20%.

The confidence level α for the $CVaR_\alpha$ measure is equal to 0.10, as suggested in Jian Z et al. [18].

For each out-of-sample month, we generate 10,000 scenarios based on the procedure described in section 2.2.1.

We preliminary introduce four alternatives for the level of severity in the definition of the idiosyncratic shocks (4) by setting δ = {25%, 50%, 75%, 100%}. However, as periods with a number of assets in distress greater than or equal to 75% hardly ever occur in our simulations, we restrict the attention on the cases with δ =25% and δ =50%.

In the experiments, we consider an initial capital W_0 of *2,000,000 €* and evaluate the transaction costs through the cost function presented in Beraldi P et al. [35]. Table 6 displays its structure.

Table 6. *Structure of the transaction costs function.*

Trading Segment (€)	Fixed Fee (€)	Proportional Costs (%)
0–7,999	40	0
8,000–49,999	0	0.5
50,000–99,999	0	0.4
100,000–199,999	0	0.25
≥ 200,000	400	0

Because standard optimization algorithms could encounter problems to optimize the proposed portfolios in an acceptable computational time, we adapted the heuristic algorithm developed in Kaucic M et al. [8] to approximate the global optimum of the problems.

3.3. Ex-post Comparisons

First, we conduct a sensitivity analysis to assess the role of the minimum guaranteed expected extra return ε on the ex-post profitability of the allocation models presented in section 2.

For each dataset, we then compare the performance of the six best benchmark-linked models with that of the EMU index and the results of the equally weighted and the risk parity portfolios. The equally weighted portfolio allocates 7.69% and 9.09% of the portfolio to every country or sector index.

Finally, we highlight the strengths and weaknesses of the best strategy based on country indices compared to the one that uses sector indices.

3.3.1. Sensitivity Analysis

By varying ε in {0, 0.1%, 0.2%, 0.4%, 0.6%, 0.8%}, we obtain six instances of each portfolio design, resulting in 36 models to optimize every out-of-sample month for each dataset. However, as the minimum guarantee ε exceeds 0.4%, the number of admissible portfolios reduces considerably in all the experiments. Thus, we focus on the results concerning the ε values less than or equal to 0.4%. Tables 10-21 in the Appendix report the ex-post results for all the analyzed models and the most significant values of the warranty ε. We can observe no clear relationship between the performance of a given strategy and the value of the requested extra return. Results are quite stable as ε varies and, in particular, a minimum guaranteed extra return of 0.2% provide satisfactory out-of-sample performance for all the strategies.

Table 7 shows the values of ε associated with the country-and sector-based portfolios with the best ex-post results for each tracking measure.

Table 7. *Values for the minimum guaranteed expected extra return ε.*

	Countries	Sectors
TE	0	0.2%
TE^-	0.4%	0.4%
CVaR	0	0.2%
$CoETL^{25\%}$	0	0.2%
$CoETL^{50\%}$	0.2%	0.4%
C_bVaR	0.4%	0.2%

In general, investment policies involving country indices achieve the best performance for values of the minimum guarantee ε that are less than those required by the investment based on sectors. Exceptions are the strategy minimizing the downside tracking error (2), TE^-, and the investments considering the extreme market movements for the systemic shocks as given in (7), C_bVaR. The former needs ε = 0.4% for both datasets, while the latter has ε = 0.4% for country indices and ε = 0.2% for sector indices.

3.3.2. Country- VS Sector-based Investment Policies

Tables 8 and 9 display the ex-post results for the best strategies adopting regional and sectoral investment policies. In the last three columns, there are also the EMU index's performance statistics and those of the equally weighted and the risk parity portfolios.

All the benchmark-linked asset allocation models outperform the EMU index in terms of both Sharpe and Omega ratios. However, only the strategies that handle systemic instability are consistently more profitable than the rule-based weighting schemes also in terms of CAGR.

Further, the results show that investing in sector indices produces comparable or even lower losses than the EMU index.

Regardless of the investment policy adopted, the benchmark-linked strategies have a high level of diversification, similar to the risk parity portfolio, but with a lower mean turnover rate, even far below the threshold of 20% imposed in the optimization process.

On the one hand, portfolios using (1) to penalize the deviations from the benchmark give the best tracking accuracy. On the other hand, portfolios that consider systemic events exceed the results of the strategies minimizing the periods of underperformance as well as those that consider the extreme losses with respect to the benchmark.

Table 8. *Comparison of out-of-sample results for the considered strategies using country stock indexes.*

	TE	TE^-	CVaR	$CoETL^{25\%}$	$CoETL^{50\%}$	C_bVaR	EMU	EW	RP
SR	0.178	0.179	0.176	0.177	0.189	0.182	0.167	0.176	0.176
Omega	1.609	1.616	1.600	1.613	1.652	1.621	1.546	1.601	1.605
CAGR	7.902	7.757	7.609	7.991	8.871	8.646	7.363	8.467	7.181
MDD	0.541	0.556	0.554	0.564	0.555	0.578	0.537	0.569	0.546
CVaR	0.078	0.081	0.083	0.085	0.083	0.086	0.075	0.085	0.080
DI	0.971	0.976	0.976	0.983	0.981	0.982	–	1.000	0.982
TO	0.035	0.170	0.177	0.156	0.123	0.146	–	0.023	0.217

Table 9. *Comparison of out-of-sample results for the considered strategies using sectors stock indexes.*

	TE	TE^-	CVaR	$CoETL^{25\%}$	$CoETL^{50\%}$	C_bVaR	EMU	EW	RP
SR	0.186	0.176	0.179	0.202	0.196	0.193	0.167	0.185	0.211
Omega	1.634	1.590	1.603	1.697	1.682	1.654	1.546	1.632	1.737
CAGR	8.100	7.233	7.382	8.154	7.898	7.857	7.363	7.961	7.822
MDD	0.532	0.541	0.521	0.476	0.489	0.503	0.537	0.519	0.452
CVaR	0.073	0.075	0.073	0.069	0.070	0.071	0.075	0.072	0.065
DI	0.970	0.977	0.978	0.981	0.984	0.982	–	1.000	0.979
TO	0.038	0.177	0.164	0.153	0.150	0.149	–	0.023	0.204

3.3.3. Analysis of the Best Investment Models

The higher levels of turnovers for portfolios based on sectors than those based on countries can raise doubts about the profitability of the first investment policy. To clarify this point, we study the evolution of the net wealth for the best variants of the portfolios based on the CoETL measure, using country and sector indices, respectively.

Figures 1 and 2 provide corresponding charts.

On the one hand, we confirm the competitiveness of the equally weighted strategy in beating the benchmark and its capability to generate value in both investible universes as indicated in Bessler W et al. [34]. On the other hand, the risk parity portfolio based on the country asset class underperforms the EMU index, but it has results comparable to the equally weighted portfolio when the investment is based on sectors. The strategies using the information about the systemic shocks show to be the best investment choices even in terms of net wealth. They manage better the periods of market turmoil and reduce extreme losses. Indeed, they give a final wealth of 9,104,800 € when we consider the country asset class and 8,092,900 € using sectors data. At the same time, the best result produced by their competitors is 7,838,900 €, given by the sector-based equally weighted portfolio.

To provide additional insights into the performance difference between the proposed best tracking portfolios, Figure 3 directly compares the net wealth of the country-based $CoETL^{50\%}$ strategy with that of the sector-based $CoETL^{25\%}$ portfolio over the out-of-sample period.

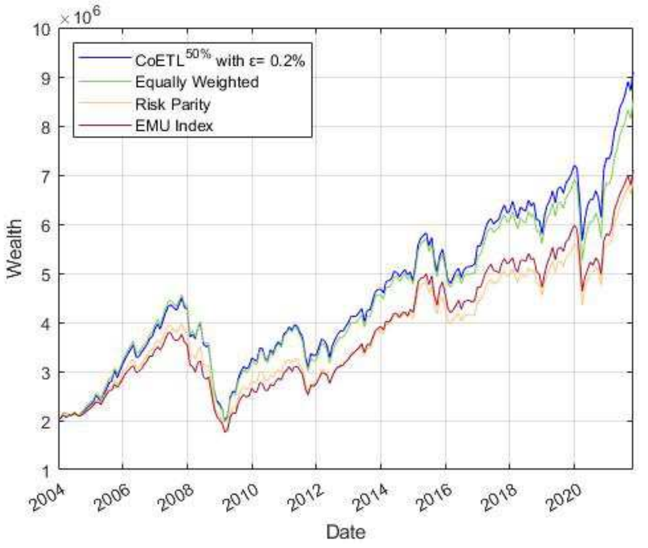

Figure 1. *Ex-post evolution of the net wealth for country-based investments.*

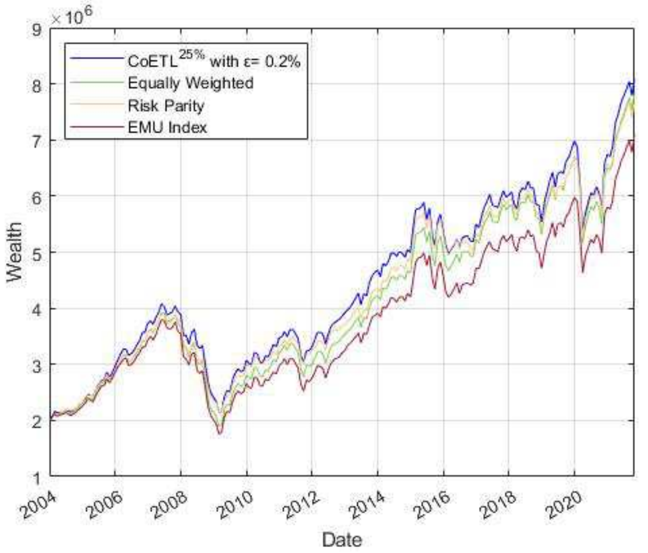

Figure 2. *Ex-post evolution of the net wealth for sector-based investments.*

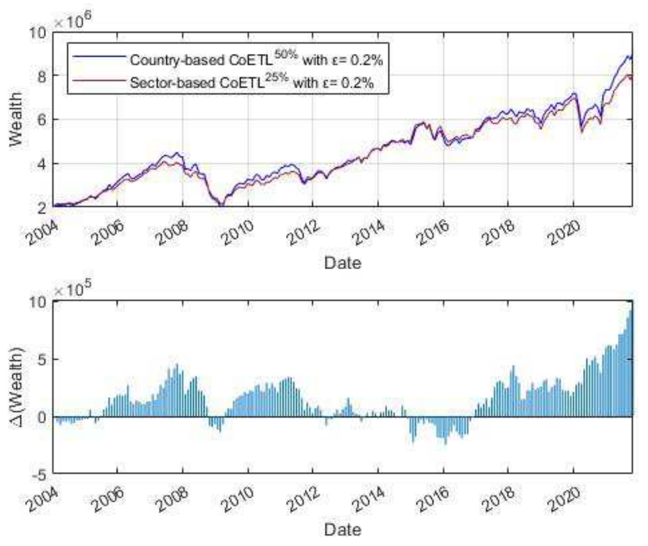

Figure 3. *Countries vs Sectors best strategies: a comparison of the differential net wealth.*

The behaviour of the two strategies is similar; however, we can see that 25% of the time, the sector-based investment produces a slightly higher wealth. Nevertheless, this outperformance is realized in the periods of marked instability, specifically in the 2008-9 subprime crisis and around the 2015-6 events (mainly, U.S. economic slow-down, the Chinese stock market crash and the Brexit).

Based on these findings, we can conclude that considering systemic shocks in developing index-linked strategies improves the out-of-sample performance.

Consistent with the literature (see, for instance, [19]), in the long run, an investment policy based on the country asset class could provide better results than an investment policy employing sectors. The higher turnover rates of the latter strategy make vain the better diversification opportunities of the sector asset class and damage its performance with respect to the more conservative investment on countries.

4. Conclusions

This study considered the enhanced index tracking problem at countries and sectors level for selected European stock indexes. We developed two novel investment strategies which include directly the information concerning the systemic financial shocks in the tracking measure to optimize. Further, we required a minimum guaranteed extra return on the benchmark, preserving an acceptable level of diversification.

The empirical results, using data for the European equity index from January 1999 to October 2021, show that the novel strategies beat the benchmark and other index-linked approaches consistently, so as the equally weighted and risk parity schemes in terms of ex-post performance ratios and net wealth, both at country and sector level. More in detail, the proposed country-based portfolio is better in most of the periods, where the sector-based performs better during the system crisis, as 2008-9 and 2015-6.

The sector-based portfolio permits a higher diversification but faces higher turnover and the consequent transaction costs; the country-based portfolio presents a lower diversification because of the higher assets correlations but requires lower transaction costs. Possible future research can try to improve the obtained results using blended portfolios that combine countries and sectors asset classes.

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The views and opinions expressed in this article are those of the authors and do not necessarily reflect the position of Generali Insurance Asset Management S.p.A.

Appendix

Table 10. *Ex-post results for country-based portfolios minimizing (1).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.178	0.176	0.178	0.171
Omega	1.609	1.598	1.606	1.581
CAGR	7.902	7.817	7.862	7.541
MDD	0.541	0.544	0.542	0.544
CVaR	0.078	0.079	0.079	0.080
DI	0.971	0.972	0.972	0.971
TO	0.035	0.044	0.045	0.053

Table 11. *Ex-post results for country-based portfolios minimizing (2).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.170	0.176	0.169	0.179
Omega	1.577	1.608	1.577	1.616
CAGR	7.408	7.742	7.401	7.757
MDD	0.577	0.570	0.565	0.556
CVaR	0.083	0.083	0.084	0.081
DI	0.981	0.978	0.981	0.976
TO	0.175	0.169	0.172	0.170

Table 12. *Ex-post results for country-based portfolios minimizing (3).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.176	0.174	0.175	0.173
Omega	1.600	1.595	1.590	1.592
CAGR	7.609	7.629	7.534	7.522
MDD	0.554	0.560	0.559	0.568
CVaR	0.083	0.082	0.082	0.083
DI	0.976	0.981	0.979	0.979
TO	0.177	0.169	0.172	0.176

Table 13. *Ex-post results for country-based portfolios minimizing (5) with δ equal to 25%.*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.177	0.176	0.166	0.174
Omega	1.613	1.598	1.569	1.595
CAGR	7.991	7.933	7.480	7.873
MDD	0.564	0.554	0.584	0.567
CVaR	0.085	0.083	0.086	0.085
DI	0.983	0.981	0.984	0.987
TO	0.156	0.149	0.149	0.158

Table 14. *Ex-post results for country-based portfolios minimizing (5) with δ equal to 50%.*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.180	0.174	0.189	0.170
Omega	1.628	1.599	1.652	1.575
CAGR	8.393	8.108	8.871	7.880
MDD	0.570	0.555	0.555	0.580
CVaR	0.084	0.085	0.083	0.086
DI	0.982	0.979	0.981	0.981
TO	0.129	0.116	0.123	0.127

Table 15. *Ex-post results for country-based portfolios minimizing (7).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.176	0.171	0.179	0.182
Omega	1.599	1.577	1.616	1.621
CAGR	8.317	7.970	8.398	8.646
MDD	0.580	0.579	0.583	0.578
CVaR	0.087	0.087	0.086	0.086
DI	0.982	0.984	0.986	0.982
TO	0.148	0.153	0.162	0.146

Table 16. *Ex-post results for sector-based portfolios minimizing (1).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.176	0.177	0.186	0.175
Omega	1.586	1.592	1.634	1.587
CAGR	7.513	7.619	8.100	7.575
MDD	0.540	0.541	0.532	0.532
CVaR	0.073	0.073	0.073	0.073
DI	0.972	0.972	0.970	0.974
TO	0.035	0.032	0.038	0.033

Table 17. *Ex-post results for sector-based portfolios minimizing (2).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.175	0.174	0.173	0.176
Omega	1.589	1.587	1.580	1.590
CAGR	7.143	7.124	6.928	7.233
MDD	0.530	0.539	0.523	0.541
CVaR	0.074	0.075	0.073	0.075
DI	0.977	0.979	0.979	0.977
TO	0.166	0.173	0.160	0.177

Table 18. *Ex-post results for sector-based portfolios minimizing (3).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.171	0.177	0.179	0.179
Omega	1.572	1.595	1.603	1.605
CAGR	6.964	7.129	7.382	7.376
MDD	0.533	0.525	0.521	0.533
CVaR	0.075	0.074	0.073	0.073
DI	0.982	0.979	0.978	0.979
TO	0.178	0.176	0.164	0.159

Table 19. *Ex-post results for sector-based portfolios minimizing (5) with δ equal to 25%.*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.194	0.187	0.202	0.186
Omega	1.670	1.629	1.697	1.624
CAGR	7.937	7.636	8.154	7.361
MDD	0.517	0.523	0.476	0.498
CVaR	0.072	0.071	0.069	0.070
DI	0.983	0.981	0.981	0.979
TO	0.156	0.153	0.153	0.161

Table 20. *Ex-post results for sector-based portfolios minimizing (5) with δ equal to 50%.*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.181	0.190	0.182	0.196
Omega	1.611	1.658	1.622	1.682
CAGR	7.254	7.792	7.374	7.898
MDD	0.494	0.512	0.535	0.489
CVaR	0.071	0.071	0.073	0.070
DI	0.983	0.984	0.982	0.984
TO	0.142	0.147	0.143	0.150

Table 21. *Ex-post results for sector-based portfolios minimizing (7).*

ε	0.0%	0.1%	0.2%	0.4%
SR	0.186	0.192	0.193	0.187
Omega	1.643	1.664	1.654	1.643
CAGR	7.634	7.771	7.857	7.626
MDD	0.530	0.509	0.503	0.519
CVaR	0.073	0.071	0.071	0.071
DI	0.983	0.981	0.982	0.984
TO	0.148	0.159	0.149	0.152

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