Portfolio optimization and index tracking for the shipping stock and freight markets using evolutionary algorithms

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Abstract

This paper reproduces the performance of an international market capitalization shipping stock index and two physical shipping indexes by investing only in US stock portfolios. The index-tracking problem is addressed using the differential evolution algorithm and the genetic algorithm. Portfolios are constructed by a subset of stocks picked from the shipping or the Dow Jones Composite Average indexes. To test the performance of the heuristics, three different trading scenarios are examined: annually, quarterly and monthly rebalancing, accounting for transaction costs where necessary. Competing portfolios are also assessed through predictive ability tests. Overall, the proposed investment strategies carry less risk compared to the benchmark tracked indexes while providing investors the opportunity to efficiently replicate the performance of both the stock and physical shipping indexes in the most cost-effective way.

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1. INTRODUCTION

Shipping stocks and the shipping industry should be more closely followed by investors for a number of different reasons. Among them are the underlying economic fundamentals of the shipping industry. Global shipping and the price that industrial companies are willing to pay to transport goods across the world are good indicators of the supply and demand for international trade. As the demand for international trade is directly linked to economic growth around the world (Kavussanos and Alizadeh, 2002; Stopford, 2009), shipping is often used as an economic indicator (Kilian, 2009). Second, the massive wave of shipping initial public offerings (IPOs) at the beginning of the second millennium resulted in the shipping industry gaining a higher profile in the global investment stage. Such exposure has made shipping companies a target of private equity and big institutional interest, and this is well documented by the institutional ownership in shipping stocks[1]. Furthermore, over the past years, the increase in the number of analysts covering shipping stocks may be another indication that shipping stocks and the shipping industry are increasingly regarded by investors as a mainstream investment opportunity rather than a niche sector for just a few specialized investors (Grammenos and Papapostolou, 2012).

The aforementioned issues provide the incentive of this paper to devise a sound investment strategy involving shipping stocks, by addressing the index tracking problem for both stock and physical shipping indexes. To this end, we apply two popular evolutionary algorithms, namely the differential evolution (DE) algorithm developed by Storn and Price (1995) and a genetic algorithm (GA; Holland, 1975) to address the index tracking problem in the global shipping equity markets, as represented by a market-capitalization shipping index, constructed by 95 shipping stocks listed on 19 stock exchanges. Our approach gives the option to US investors, who have limited access to any of the stocks comprising the shipping index, to invest in a portfolio that closely replicates its performance, has no exchange rate risk and includes only a small pre-specified number of stocks. In particular, the performance of the index is reproduced by investing in US shipping stocks.

To our knowledge, the current literature is mainly concentrated on the index tracking problem with respect to equity indexes. This paper is the first to attempt to track the performance of

[1] For instance, as of March 2010, Overseas Shipholding Group had 387 institutional investors with their share in the company accounting for 88.82%. Other notable examples are Genco Shipping & Trading, Alexander & Baldwin Inc. and Horizon Lines Inc. where the holdings of institutional investors were 85.05%, 76.42% and 90.90%, respectively (Source: Thomson Reuters).

the physical shipping market, as represented by the Baltic Dry Index (BDI) and the Baltic Dirty Tanker Index (BDTI). This has important practical implications for investors who want to participate in the physical shipping market but often find themselves with limited investment options, as in the case of pension funds. The two physical indexes are provided by the Baltic Exchange, while the International Maritime Exchange (IMAREX) and investment banks also offer futures contracts on these indexes. However, access to these products is limited with potential frictions for investors. Investing in futures contracts entails higher risk due to the highly volatile nature of the physical shipping markets, expiration effects and the high monthly rollover cost, which is necessary to maintain a long-only position on the index.

In particular, nearby contracts must be sold and contracts with later deliveries must be purchased. This process is referred to as “rolling”, and irrespectively of whether the futures curve is in backwardation or contango, investors need to actively trade and accept the market prices for both transactions, i.e. the liquidation of the current-month contract and the purchase of the next-month contract. As a result, the frequent rolling-forward makes it very expensive to follow an index replication strategy using exchange-traded futures. Moreover, shipping futures contracts expire less frequently compared to financial contracts, thus rolling forward can be more costly and vulnerable to longer duration and thinner liquidity. Finally, long-only futures indexes offer little protection against any abrupt price changes, as they do not provide the possibility of short-selling, and most of them are rebalanced only once a year.

Two additional unique aspects of this paper involve the analysis of different rebalancing settings on the performance of the tracking portfolios, as well as the consideration of the data snooping bias. A sound rebalancing framework is essential to ensure that the portfolio maintains the optimal relative allocation over time, given that, if correlations of the assets comprising the tracking portfolio are time-varying, the structure of the fund must adjust to accurately reflect the benchmark index. Moreover, rebalancing deals with potential weight instability due to, for example, structural changes in the fluctuations of prices. The aim is to provide investors and financial institutions with valuable information on whether regular revision of the portfolio formation is able to exploit the arrival of news. This issue is examined empirically in this study, while at the same time evaluating how much transaction costs affect performance. Besides contrasting rebalancing strategies to replicate the considered equity and physical shipping indexes, it is also interesting to identify which subset of the stocks is more likely to effectively mimic each respective benchmark index. Thus, tracking ability is tested while controlling for data snooping. The latter is achieved by applying Hansen's (2005) superior predictive ability test to examine whether the best performer is indeed superior compared to the competing subsets of stocks. The goal is to determine the statistical significance of the empirical findings in three aspects, namely the efficiency of the algorithms employed, the performance of the index tracking strategies and the implemented rebalancing schemes.

In terms of investment opportunities, the shipping industry can offer investors a number of choices. These may range from debt and derivative related instruments (Grammenos et al., 2008; Kavussanos and Visvikis, 2006) to equity investments in publicly listed shipping companies and shipping-specific funds (Syriopoulos and Roumpis, 2009; Drobetz et al., 2010; Merikas et al., 2010; Drobetz and Tegtmeier, 2011). The investment strategies proposed in this paper give investors the opportunity to replicate the performance of both stock and physical shipping markets by investing in easily accessible stocks. Investors may also take short positions when they believe that the maritime sector is entering a downturn. Additionally, fund managers can benefit from the proposed strategies when they overweight or underweight specific sectors according to their market and economic outlook. Risk-averse investors who wish to track the performance of the highly volatile maritime industry can also invest in the proposed portfolios that carry lower volatility. Finally, there is a plethora of mutual funds and Exchange Traded Funds (ETFs) that track passive benchmarks of stock, commodity, business sector, country, regional indexes, etc. The results of the paper could encourage mutual and hedge fund managers to recognize the importance of the maritime sector and set up similar funds[2] that will track the proposed shipping equity and physical indexes. To that end, our methodology puts forward an effective and at the same time cost-effective way to operate such a fund.

The structure of the paper is as follows. The next section presents a literature review on index tracking methodologies for passive investment strategies, together with a description of the problem formulation, the solution algorithms and the superior predictive ability test methodology. Section 3 gives an explanation of the data and the construction of the market capitalization shipping index. In section 4, the empirical results are discussed. Finally, section 5 concludes the paper.

[2] A shipping ETF can be used by ship owners or other market participants of the maritime and transportation industry, to complete parts of their existing portfolios or to perform tactical investment strategies.

2. INDEX TRACKING FOR PASSIVE INVESTMENT STRATEGIES

Financial portfolio management is implemented by using active or passive strategies[3]. On the one hand, under the active strategy, portfolio managers assume that markets are not perfectly efficient and that there is room for exploiting any disequilibrium or mispricing conditions. As a result, portfolio managers will attempt to pick high-performing stocks and/or time their buy/sell decisions in order to outperform the market or other investment options. On the other hand, a passive strategy assumes that the markets are efficient and cannot be beaten in the long run; hence, the main activity of passive portfolio managers is to achieve the same or at least very similar returns of a pre-specified market index. One of the most popular forms of passive trading strategies is index tracking, which attempts to reproduce the performance of a benchmark index, with portfolio managers having the option to choose between full or partial replication schemes[4].

2.1. Problem formulation

In the search for optimally replicating an index, different studies (Gaivoronski et al., 2004; Frino and Gallagher, 2001) focus on the performance deviations of the tracking portfolio, i.e. the tracking error. Additionally, single-factor and Markowitz models (Larsen-Jr and Resnick, 1998; Rohweder, 1998; Wang, 1999) have been used to replicate the performance of an index. Furthermore, the use of the cointegration concept in building portfolios for index tracking is highlighted by Alexander and Dimitriu (2002) and Dunis and Ho (2005).

In this study we measure tracking error through the Root Mean Squared Error (RMSE) criterion. In particular, we assume that there exist price data on N stocks and the price of an index over an (in-sample) time period $[1, 2, \ldots, T]$. The goal is to create a tracking portfolio consisting of at most K stocks ($K < N$) that replicates, as closely as possible, the index for an (out-of-sample) period $[T+1, T+\Delta t]$. The replication error of the tracking portfolio is defined as follows:

[3] For a comparison between active and passive strategies see Sharpe (1991); Malkiel (1995); Sorenson et al. (1998); Barber and Odean (2000); Frino and Gallagher (2001); Beasley et al. (2003); Konno and Hatagi (2005); Maringer and Oyewumi (2007).

[4] Full replication requires the purchase of all stocks in an index. Alternatively, managers can hold portfolios that include only the stocks they consider to be replicating the index most effectively. Furthermore, the full replication method is associated with higher transactions costs (Beasley et al., 2003).

$$RMSE = \sqrt{\sum_{t=1}^{T} \left(r_t - R_t\right)^2 / T} \tag{1}$$

where r_t and R_t are the returns for the tracking portfolio and the index, respectively.

Except for the replication error, the return of the tracking portfolio is also of interest. To this end, we consider the mean excess return (ER) over the benchmark index, defined as follows:

$$ER = \sum_{t=1}^{T} \left(r_t - R_t\right) / T. \tag{2}$$

Let P_{it} denote the price of stock i at time t, C the available capital and x_i the number of units bought from stock i. The complete formulation of the objectives and constraints used to solve the index tracking problem can then be expressed as follows:

Minimize: $f = \lambda \times RMSE - \left(1 - \lambda\right) \times ER$ (3)

Subject to:

$$\sum_{i=1}^{N} P_{iT} x_i = C \tag{4}$$

$$z_i \varepsilon C \leq P_{iT} x_i \leq z_i C \qquad \forall i = 1, \ldots, N \tag{5}$$

$$\sum_{i=1}^{N} z_i \leq K \tag{6}$$

$$x_i \geq 0, \qquad z_i \in \left\{0, 1\right\} \qquad \forall i = 1, \ldots, N \tag{7}$$

where $0 \leq \lambda \leq 1$ is a user-defined parameter that outlines the trade-off between the two objectives (tracking error and excess return). In the case $\lambda = 1$, the tracking portfolio has as its main objective to minimize the tracking error (pure index tracking), whereas when $\lambda = 0$, the portfolio's main goal is to maximize the excess return. Constraint (4) guarantees that the value of the portfolio at the end of the in-sample period is equal to the available capital C. This budgetary limitation ensures that for all alternative tracking portfolios an identical amount C is invested at the beginning of the out-of-sample period. Constraint (5) associates a binary variable z_i to each stock i, which is used to consider whether stock i is included in the tracking portfolio ($z_i = 1$) or not ($z_i = 0$). The parameter ε is used to impose a lower bound on the proportion of the capital invested in each stock (in this study ε is equal to 0.01). Finally, constraint (6) defines the maximum number of stocks K that can be included in the tracking portfolio.

2.2. Evolutionary solution techniques

The optimization model (3)-(7) is a complex combinatorial problem, which is difficult to solve with analytical techniques. Thus, evolutionary algorithms have become particularly popular in this context. Evolutionary algorithms were first used for addressing the index tracking problem by Goldberg (1989), who apply a genetic algorithm for index replication. Recent applications of genetic algorithms in index tracking and portfolio optimization can be found in the works of Oh et al. (2005), Chang et al. (2009) and Soleimani et al. (2009). Beasley et al. (2003) propose an evolutionary population heuristic, accounting for transaction costs and the possibility for revision of the tracking portfolio. Their results indicate that deriving the optimal portfolio directly from past data and not from the distribution of stock returns ultimately achieves better results. Maringer and Oyewumi (2007) apply DE for tracking the Dow Jones Industrial Average assuming different cardinality constraints in their selected portfolios. They report that the maximum number of stocks included in the tracking portfolio must be roughly 50% of the benchmark index to achieve good results; any additional stocks only marginally improve the algorithm's performance. The DE algorithm has also been used in other recent studies using hybrid and multi-objective schemes (Krink et al., 2009; Krink and Paterlini, 2011), as well as in the context of loss aversion (Maringer, 2008) and mutual fund replication (Zhang and Maringer, 2010). Other recently proposed algorithmic procedures include immune systems (Li et al., 2011), hybrid algorithms (Ruiz-Torrubiano and Suárez, 2009; Scozzari et al. 2012), robust optimization (Chen and Kwon, 2012) and mixed-integer programming formulations (Canakgoz and Beasley, 2008; Stoyan and Kwon, 2010). An overview of different methods can be found in Woodside-Oriakhi et al. (2011).

In the context of this study, the DE algorithm and a genetic algorithm (GA) are employed. Both algorithms are well established in the computational intelligence literature, easy to implement and (as the above brief literature overview indicates) well suited for complex financial optimization problems, particularly in the context of index tracking and constrained portfolio optimization. The application of both algorithms enables the examination of the robustness of the results under different solution approaches.

GAs are probably the most popular evolutionary techniques. GAs are computational procedures that mimic the process of natural evolution for solving complex optimization problems (Goldberg, 1989). A GA implements stochastic search schemes to evolve an initial population (set) of solutions through selection, mutation and crossover operators until a good solution is reached.

Similarly to the GA framework, DE is also a stochastic optimization method. DE was developed by Storn and Price (1995) as an alternative to existing metaheurtistic approaches, and it is well suited to continuous optimization problems. According to Storn and Price (1997), compared to other rival approaches, the main advantages of DE include its fast convergence, the use of a small set of tuning parameters, its reduced sensitivity to the initial solution conditions and its robustness. Overall, comparisons on various benchmark problems show that DE is superior when compared to other evolutionary algorithms (Sarker et al., 2002; Sarker and Abbass, 2004).

Both algorithms are implemented with a real-valued solution representation scheme. In particular, each solution is represented by a real-valued vector $\mathbf{x} \in \mathbb{R}^N$, where N is the number of stocks in the sample. The K largest positive elements of $\mathbf{x}$ are used to identify the stocks comprising the tracking portfolio[5], and after normalization (to sum up to 1) they define the corresponding stock weights ($w_1, \ldots, w_N$). The number of units bought from each stock can then be specified as $x_i = Cw_i / P_{iT}$. Appendix A provides a brief description of the implementations of the two evolutionary methods used in this study. The parameters of the algorithms were calibrated after experimentation in order to achieve a good balance between the quality of the results and the solution times. The selected parameters are summarized in Appendix 1, Table A1.

2.3 Superior predictive ability test

In the analysis of time series data, an important issue that needs to be considered is that of data snooping bias. According to Sullivan et al. (1999) and White (2000), data snooping occurs when a single data set is used for model selection and inference. When testing different investment strategies, there is a probability of having a given set of results purely due to chance rather

[5] If the number of positive elements of **x** is smaller than *K*, then all positive elements of **x** are used.

than these being truly based on the actual superior predictive ability of the competing strategies. Predictive ability tests have been extensively used in the empirical financial economics literature in various aspects, such as volatility forecast comparison (Hansen and Lunde, 2005), evaluation of risk management loss functions (Bao et al., 2006) and evaluation of trading rules' performance (Sullivan et al., 1999, Hsu et al., 2010, and Neuhierl and Schlusche, 2011), among others. For instance, Alizadeh and Nomikos (2007) apply bootstrap techniques to approximate the empirical distribution of Sharpe ratios and test different trading rules in the sale and purchase market for ships.

To account for potential data mining and evaluate the performance of the tracking portfolios in a statistically meaningful way, we employ the test of superior predictive ability (SPA) proposed by Hansen (2005) as a complementary framework to the investment strategy performance evaluation procedure. The SPA test allows for a comparison of the out-of-sample performance of one benchmark model to that of a set of rival models. Empirically, it consists of the following: Let $LF_{t,k}$ denote a loss function (for instance squared tracking error) between a prediction r_t against an actual measurement R_t under a given model k. In our case, r_t and R_t are the returns at time t for the tracking portfolio and the index, respectively. Setting $k=0$ for the considered benchmark model, alternative models $k=1,\ldots,l$ can be compared via the loss differential $f_{t,k}=LF_{t,0}-LF_{t,k}$, for $t=1,\ldots,n$, where n is the number of days of the out-of-sample period.

To test whether a benchmark tracking portfolio is outperformed by any other tracking portfolio, the null hypothesis is set as $H_0:\max_k E(f_{t,k})\leq 0$. The rejection of the null provides evidence that at least one tracking portfolio significantly outperforms the benchmark. Although the expectation of $f_{t,k}$ is not known, by the law of large numbers it can be consistently estimated with the sample mean $\overline{f}_k$. White (2000) suggests a reality check (RC), where the statistic is $RC=\max_k(n^{1/2}\overline{f}_k)$. However, one major drawback is that the *RC* test depends heavily on the set of rival models. As such, if poor or irrelevant models are included in the dataset, the test is inconsistent and leads to frequent acceptance of the null hypothesis, i.e. it is conservative. As a solution, Hansen (2005) proposed the following more robust studentized statistic:

$$SPA = \max_k \left(\frac{n^{1/2} \overline{f}_k}{\hat{\omega}_{kk}} \right) \quad (8)$$

where $\hat{\omega}_{kk}$ is a consistent estimate of the variance of $n^{1/2} \overline{f}_k$, $\omega_{kk}^2 = \lim_{N \to \infty} var(n^{1/2} \overline{f}_k)^n$. A consistent estimator of ω_{kk} and the *p*-value of SPA statistic can be obtained via a stationary bootstrap[6] procedure of Politis and Romano (1994). More details on this procedure are outlined in Hansen (2005) and Hansen and Lunde (2005).

In short, to discount the possibility that the performance amongst the selected tracking portfolios could be due to data snooping bias, the bootstrap version of Hansen's (2005) SPA test is implemented. To this end, by grouping the set of tracking portfolios, we conduct a battery of tests from different perspectives, such as efficiency of the replication algorithms, e.g., DE vs. GA, the rebalancing schemes, etc. (see section 4 for more details).

3. DATA AND BENCHMARK SHIPPING INDEXES

The dataset includes quotes for 160 stocks and two physical shipping indexes, the Baltic Dry Index (BDI) and the Baltic Dirty Tanker Index (BDTI). Daily closing prices were downloaded from Datastream for the period February 15, 2006 to February 17, 2012, leading to a total of 1,514 trading days after filtering out bank holidays. For the computational analysis, the in-sample period consists of the first two years of the sample, and the remaining four years are withheld to perform the out-of-sample analysis.

The stock data can be divided into two groups: the constituent stocks of the Dow Jones Composite Average[7] ($N = 65$ stocks), and the stocks of the constructed "Shipping" index

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[6] The stationary bootstrap re-samples blocks of random length from the original data to accommodate serial dependence, where the block length follows a geometric distribution and its mean value equals $1/q$. Obviously, for $q = 1$ the problem is reduced to the ordinary bootstrap, which is suitable for series of negligible or no dependence. In this paper, we use $q = 0.25$ although we also perform a sensitivity analysis to identify potential patterns, if any. The results show no sensitivity, and similar qualitative outcomes are obtained for $q = \{0.1, 0.15, 0.2, 0.25, 0.5\}$. For more technical details on the implementation of the stationary bootstrap and the reality check, the reader is referred to Sullivan et al., 1999; Appendix C, pp 1689-1690. In what follows, we use 5,000 random paths of portfolio returns. Having obtained the simulated paths, we finally construct the SPA statistic and obtain the p-value of the null.

[7] The reason we use Dow Jones Composite Average is mainly due to investment restrictions of some large hedge funds/investors. For example, certain funds only invest in stocks with a minimum market capitalization of $1billion. Several studies (see Gompers and Metrick, 2001 among others), find that due to legal concerns institutional investors prefer large-cap and liquid stocks. As such, our Dow baskets give the opportunity to track the shipping stock market using larger-cap stocks from other industries.

($N=95$). The latter is an arithmetic weighted index, where the weights are assigned according to the market capitalization of each firm. It includes stocks of publicly listed international maritime companies that derive their revenues primarily from seaborne transportation (more than 80% during the sample period). The refined and final sample consists of daily data for 95 shipping stocks that are traded on 19 different stock exchanges in Europe, Asia and the Americas. Table 1 describes the composition of the "Shipping" index. The average weights of the constituents along with their associated standard errors are also reported. To ensure that no company has an excessive undesirable impact on the index, constituents are confined to a maximum weight of 10%. Any excess weight resulting from the imposed upper bound is distributed proportionately among the remaining stocks, consistent with their individual market capitalization.

In the empirical analysis, the market-capitalisation-weighted equity index (henceforth "Shipping" index) and two physical shipping indexes, BDI and BDTI, are to be tracked. DE and GA are both employed to replicate the performance of the indexes by using a subset of stocks included either in the Dow Jones Composite Average or the "Shipping" index (henceforth Dow and Shipping baskets). The stocks picked from the "Shipping" index are used to form the Shipping baskets. Likewise, stocks pulled out from the Dow index form the Dow baskets. For the period examined, the average market capitalization of the "Shipping" index components ranges from \$6.7 million to \$18.6 billion; the corresponding figure for Dow Jones is \$1.4 to \$388 billion.

Our investment strategies are devised from the standpoint of a US investor with a dollar-denominated portfolio. In particular, we examine opportunities in a portfolio composed of either solely shipping US stocks (Shipping basket) or US stocks in general (Dow basket). This way, we track the performance of domestic, foreign and physical markets seeking to generate a similar or improved return-risk profile.

4. EMPIRICAL RESULTS

This section presents the empirical findings on index tracking in the shipping stock and physical markets. To test the performance of the heuristics, three different scenarios are examined. In the first one, the algorithms are tested with rebalancing the tracking portfolios for the out-of-sample period on an annual basis. In the second scenario, the portfolios are rebalanced quarterly, whereas in the third scenario, the portfolios are rebalanced on a monthly basis. The main purpose of testing these three scenarios is to examine whether the inclusion of additional information into the index-tracking algorithms—by rebalancing the portfolio more frequently—is actually more rewarding. In all rebalancing settings, transaction costs are taken into consideration by appropriately adjusting the returns; a 0.75% cost is assumed for each transaction.

The cumulative returns of the indexes are rebased to 100, and for illustration purposes they are presented in Figures 1-2. Figure 1 plots the "Shipping" index against three widely known stock indexes (Dow Jones Composite Average, S&P 500 and NASDAQ 100) and one commodity index (Dow Jones-UBS). The indexes exhibit similar behaviour, with the "Shipping" index fluctuating in higher levels, especially before 2009, and also experiencing a more pronounced collapse during the 2008 economic recession. Figure 2 displays the relative performances of the "Shipping", BDI and BDTI indexes. Although the indexes exhibit comparable trends in the long-run, differences are markedly evident in the short-run. Clearly, the two physical indexes involve higher levels of volatility with relatively more frequent and large transitory short-run deviations.

The initial investment budget of our experiments is set equal to $C = \$100,000$. All tracking portfolios include at most K stocks, where K can be either 5 or 10. In addition, three different trade-off profiles between tracking error and excess return are considered by adjusting the parameter λ in equation (3); the values of λ represent different investment attitudes toward portfolio construction, and are set equal to 0.6, 0.8 and 1. For example, in the case $\lambda = 1$, the investor is interested utterly in pure replication of the index, irrespective of its performance. As λ decreases, the investor is willing to deliberately accept a fraction of the tracking error, in view of an optimum return-error combination. Implementation of the DE and GA algorithms is repeated for a series of runs; the ensuing analysis is based on the best reported solution (where the objective function is minimized) for each particular set of parameters (see Appendix 1, Table A1).

Overall, in terms of tracking errors and excess returns, both DE and GA offer an analogous outcome; yet, results tend to favor the GA, especially when the Dow basket acts as the tracker. In what follows, we first review the findings on the shipping stock market index tracking. Then, the experiment is extended to the shipping physical market. Finally, the tracking portfolios' key statistical properties are also discussed, including the reporting of Sharpe ratios, which put our tracking strategies into an economic perspective.

4.1 Tracking the shipping stock market

Figure 3 displays the "Shipping" index against quarterly rebalanced Dow and Shipping baskets of maximum 10 stocks ($K = 10$), with $\lambda = 1$ as constructed by the two evolutionary algorithms. These are cumulative returns of the baskets (note that these include reallocation transactions costs of 0.75% per transaction), implying that large errors have an impact throughout the entire holding period of the out-of-sample period (due to budget constraints, at each point of rebalancing the index and the tracking baskets differ). Thus, in terms of cumulative return levels some differences are evident, especially for the shipping baskets. However, both baskets seem to reasonably track the daily variations of the "Shipping" index. In addition, after the second half of 2008, the Dow basket consistently generates cumulative returns in excess of the benchmark. It should be stressed out that, although the 2008 financial crisis caused a significant downturn in the global equity markets, many shipping stocks, as represented by the constructed index and selected baskets, exhibited positive returns until the first half of 2008, reflecting the unanticipated boom in commodities and freight rates. Nevertheless, shortly after, freight rates also collapsed and shipping stocks rapidly caught up with the general down-trend. Thus, the Shipping baskets incurred substantial losses compared to the Dow baskets (see Figure 3).

Table 2 documents the out-of-sample daily root mean squared errors and mean excess returns for the constructed DE and GA baskets. For all K, λ combinations and under all rebalancing scenarios, Shipping and Dow baskets are marginally different; the average of the Dow basket RMSEs is 0.1528 compared to 0.01526 for the Shipping basket. In terms of RMSE, the best tracker is the Shipping GA basket with (K, λ) = (10, 0.6), when weights are rebalanced on a monthly basis (Panel C, RMSE = 0.01416). This can be attributed to the high correlation between the Shipping basket and the benchmark, as the latter basket selects stocks from the constituent list of the "Shipping" index. Moreover, all Shipping baskets are associated with negative excess returns[8], primarily because the shipping industry experienced an unparalleled downtrend during the examined period. The best model to minimize the objective function of Equation 3 is the Dow GA basket with monthly rebalancing and (K, λ) = (5, 0.6); this can be calculated from the information presented in Table 2 (Eq. 3: f = $\lambda RMSE\text{-}(1\text{-}\lambda)(ER)$=0.6(0.01482)-(1-0.6)(0.0751/100)=0.0086).

[8] Investors who would have taken short positions in the Shipping basket would realize the highest excess returns.

Another interesting observation involves the rebalancing frequency of the investment strategies. On average, rebalancing the baskets' weights leads to improved RMSEs. For instance, looking at the Shipping GA basket, increasing the rebalancing frequency from annually (quarterly) to monthly causes a 3.4 to 8.6% (2.4 to 5.7%) improvement in the RMSEs. The subsequent effect from quarterly to monthly is less prominent. Monthly rebalancing produces the best results in terms of tracking errors, apart from the Dow DE baskets where annual portfolio revisions seem superior. Still, frequent rebalancing overall trims down excess returns, mainly due to increased transaction costs. Other studies such as Dunis and Ho (2005) noted that a quarterly portfolio update is preferable to monthly or annual reallocations, where the former has the shortcoming of high transaction costs and the latter is too restrictive. Thus, it is up to the investors' risk-return appetite to decide whether rebalancing the portfolio monthly—which comes at an extra cost—is better than less frequent revisions.

For pure replication of the benchmark index, i.e. $\lambda = 1$, the lowest tracking error is achieved by the Shipping GA baskets under all rebalancing strategies. Moreover, different values of λ do not impact RMSEs much. Turning to the mean excess returns, these are maximized for $\lambda = 0.6$ as expected, as the optimization procedure assigns more weight to the target for excess return. This finding is more pronounced for monthly reallocations; however, any exceptions are not surprising as the reported metrics for the set of investment strategies are based on the out-of-sample period. Regarding the efficiency of DE and GA, the latter is associated with lower tracking errors and higher excess returns; this is evident when baskets' readjustments take place more often, especially in the monthly scheme.

Furthermore, Table 2 presents the results of the SPA tests. We conduct a battery of tests by grouping the set of tracking portfolios from various aspects. The first objective is to determine the relative efficiency of the algorithms employed, i.e. whether the tracking errors (RMSEs) are significantly better for the DE or GA of the same parameters (K and λ), baskets (either Dow or Shipping) and rebalancing periods, using pairwise comparisons. RMSE values with the superscript "a" attached to them denote the tracking portfolios with significantly better performance compared to the competing algorithm. Results show that GA significantly outperforms the DE (24 out of 36 cases), especially for quarterly and monthly rebalanced baskets. The second objective is to determine the relative efficiency of the replication strategies, i.e. to identify if a model consistently surpasses the others for any given set of K and λ parameters and at any given rebalancing scheme; that is, at each row of Table 2. RMSE values with the superscript “b” attached to them denote the tracking portfolios with significantly better performance compared to the competing baskets and algorithm, using joint comparison of four models per test. Yet, no significantly lower errors can be observed for any particular basket at each set of K, λ and rebalancing period at 5% level (henceforth the considered level of significance examined is 5% for all SPA tests). This implies that nominal RMSE values are statistically equivalent. In addition, the above tests are also performed when excess returns (ER) are considered as the objective (and not the RMSEs). ER values with superscripts “a” or “b” attached represent tracking portfolios with significantly higher returns compared to the rival algorithm or the rival tracking basket, respectively. Table 2 asserts that the GA is more effective (14 out of 24 cases), whereas only the Dow GA basket manages to outperform all, the Dow DE, Shipping GA and Shipping DE baskets, at certain cases (9 out of 18).

Finally, another objective is to verify the relative efficiency of the rebalancing scenarios, i.e. whether more frequent portfolio revisions lead to significantly lower RMSEs and/or higher ERs, for each given basket; that is, at each column of Table 2. For that reason, joint comparisons of 13 strategies are implemented, e.g. annually rebalanced Dow basket with certain K and λ parameters, all monthly and quarterly frequencies of the Dow basket and for all K and λ. Results are not presented here and are available from the authors upon request; however, findings are consistent. Regarding RMSEs, monthly rebalancing generates significantly lower values; this holds for all GA baskets as well as for the DE baskets with $K = 5$. Regarding ERs, overall, monthly rebalancing produces significantly lower returns, and results are stronger for the DE baskets.

4.2. Tracking the shipping physical market

The physical shipping index tracking results are reported in Table 3. Clearly, the Dow baskets outperform the Shipping baskets with an average RMSE reduction close to 14%. Moreover, the Dow baskets accomplish relatively higher excess returns in all cases; an approximate average increase of 7.6 basis points in ER. Once more, the GA provides a superior combination of excess returns and RMSEs; on average, excess returns are 1 basis point higher and RMSEs are 2.5 percentage points lower compared to the DE algorithm. The best out-of-sample BDI tracker is the Dow basket with (K,λ) = (5, 0.6) for monthly rebalancing (Panel A, RMSE = 0.0294); for

BDTI it is the Dow basket with (K , λ) = (10, 0.8) under the same rebalancing frequency (Panel B, RMSE = 0.02722).

Similar to the shipping stock index tracking exercise, the baskets still generate the highest excess returns when $\lambda = 0.6$, in line with the trade-off criterion (17 out of 24 cases for BDI and 20 out of 24 for BDTI). Once again, it is up to the investors' preferences to decide on the trade-off parameter λ. Moreover, as before, there is a negative relationship between rebalancing frequency, tracking errors and excess returns; frequent revisions increase accuracy at the cost of higher transaction fees. On the other hand, increasing the rebalancing frequency has a marginal effect. Finally, should the investor increase the number of stocks included in the basket from $K = 5$ to $K = 10$, the outcome will be only trivially altered. Overall, as highlighted in Table 3 (Panels A and B) the best model to minimize the objective function of Equation 3 is the Dow GA basket with monthly rebalancing and (K , λ) = (5, 0.6), as was the case when tracking the "Shipping" index.

The results of the SPA tests are also displayed in Table 3. It can be observed that both BDI and BDTI can be tracked by the Dow GA baskets with significantly lower tracking errors (superscript "b"), while GA is generally more accurate (superscript "a"). As for excess returns, there are only few cases where significance is achieved; 24 out of 72 when comparing the algorithms and 15 out of 72 when comparing the baskets at any given set of parameters K, λ and rebalancing scenarios (however, results are stronger for monthly rebalancing frequencies: 3 out of 6 for BDI and all 6 for BDTI). Overall, Dow GA baskets present better ability of replicating the physical indexes. This evidence is unanimous across RMSEs in all rebalancing scenarios; for excess returns it is more profound in the monthly rebalancing scheme. Finally, the findings on the relative efficiency of the rebalancing periods (available from the authors upon request) are similar to the stock index tracking problem. For BDI, regarding RMSEs (ERs) monthly (annually) rebalancing produces significantly lower (higher) figures compared to quarterly and annually (monthly and quarterly). For BDTI, results are mixed between the GA and DE. BDTI GA baskets are associated with significantly lower errors in quarterly and monthly schemes; this does not hold for DE baskets, where there is no clear winner according to the SPA tests. Still, for ERs, annually rebalanced baskets are superior.

When comparing the baskets' performance in terms of tracking the physical and shipping stock indexes, one essential remark should be made. As verified by the relatively higher tracking errors, tracking BDI and BDTI is far more challenging. Yet, the less accurate tracking performance of the physical market is not startling. It is a consequence of, first, the low correlation between the physical and financial markets and, second, the existence of diverse and unique to each market risk factors; these act as further complexities in the effort to mimic the behavior of physical quantities using financial stocks. Hence, tracking the physical indexes is more demanding because the physical and stock markets display relative autonomy in their price formation mechanisms and evolution. Figures 4 and 5 illustrate the relative performance of the Dow and Shipping baskets in tracking the BDTI and BDI under the genetic and differential evolution algorithms. As in the "Shipping" index case, note that these are cumulative returns of the baskets (including reallocation transactions costs of 0.75% per transaction) and large errors have an impact throughout the complete holding period, i.e. four years (due to budget constraints, at each point of rebalancing the index and tracking baskets are not the same).

4.3. Statistical properties and risk-return profile of the constructed portfolios

Tables 4 and 5 present key statistics of the constructed baskets, the correlation of the tracking portfolio returns with the benchmark returns and the corresponding Sharpe ratios. For comparison reasons, in Panel D of Table 4, the annualized mean and volatilities of three stock indexes (Dow Jones Composite Average, S&P 500 and NASDAQ 100) and one commodity index (Dow Jones-UBS) are also reported (see also Figure 2). When comparing the Sharpe ratios, only the commodity index has similar risk-return profile to the shipping markets (negative). The financial indexes are able to generate a better risk-return performance compared to the shipping indexes. According to the historical annualized volatilities, the "Shipping" index exhibits comparable levels of volatility with the other financial indexes; these are in the range of 26.5 to 29%. Slightly lower is the volatility of the commodity index (23.5%), whereas BDI and BDTI are associated with fairly elevated levels of volatility. This is due to changing economic and seaborne transportation patterns, international politics, technological advances, structural changes in the maritime industry and major events (canal closures, embargoes and wars); all these have created considerable uncertainty in the shipping physical markets, which strongly depend on demand and supply fluctuations in seaborne transportation. .

Next, we turn our attention to the different tracking strategies. Moving from annual rebalancing to more frequent reallocation schemes, Sharpe ratios tend to diminish, as a result of higher transaction costs. It can be argued that when rebalancing, the additional information available from the latest price data does make a difference in reducing the portfolios' volatility, but the small return deterioration outweighs the volatility benefits. Results are consistent for all cases for the risk-return trade-off λ. The best performance for the stock index tracking, in terms of Sharpe ratios, is reported for the Dow GA baskets that are rebalanced quarterly for (K, λ) = (5, 0.6). In that case the reward-to-risk ratio equals 0.414, much higher than the benchmark "Shipping" index of -0.406. Regarding the physical indexes tracking (see Table 5), the best performance is achieved by the Dow GA baskets that are rebalanced annually for (K, λ) = (5, 0.6) for both BDI and BDTI. The corresponding Sharpe ratios of the baskets are 0.357 and 0.535, whereas the benchmark Sharpe ratios are -1.317 and -0.286, respectively.

Although the Dow baskets generate positive Sharpe ratios, at least in annually and quarterly rebalancing frequencies, this does not hold for "Shipping" baskets. In general, this implies that the tracked and benchmark indexes present differences in terms of sign (Dow baskets only) and/or level. On the one hand, for the "Shipping" index differences in the level of annualized returns can be explained by the fact that shipping stock markets have been more vulnerable to the recent economic recession compared to other equity markets. Hence, shipping-related (Dow) portfolios over the out-of-sample period underperform (outperform) the benchmark stock index, as they are associated with lower (higher) annualized returns. On the other hand, physical markets have been even more susceptible to the recent economic recession, as generally both Dow and Shipping baskets outperform the benchmark in terms of Sharpe ratios and returns. Interesting is the case of the Dow baskets which often manage to achieve returns with opposite sign than that of the tracked indexes. This can be attributed to the relatively lower correlation as well as the resulting relatively lower volatilities of the Dow baskets, compared to BDI and BDTI. However, note that more frequent rebalancing, improves tracking performance.

Moreover, for all rebalancing frequencies, Dow baskets volatilities are significantly lower than the benchmark irrespective of whether this is the "Shipping" index or the BDI, BDTI (an F-test of equal variances confirms this finding). The Dow baskets experience annualized volatilities of 17% to 25%, which is less than not only all the benchmark indexes but also the Dow Jones Composite Index itself. This implies that high diversification benefits may arise, while at the same time, different combinations can be selected that offer reduced portfolio variance. In the case of the Shipping baskets, the results are similar only for the physical indexes. When tracking the “Shipping” index with US shipping stocks, no variance reduction is observed. This is not a surprising result as stocks ($K = 5$ or 10) are selected from a subset ($N = 37$) of a much wider index ($N = 95$). Thus, opportunities for potential diversification benefits are rather limited.

Several studies in the literature propose different rules for setting K. Maringer and Oyewumi (2007) argued that including roughly 50% of the available assets is suitable to get the desirable properties in the tracking portfolios. Meade and Beasley (2004) suggested that the optimum number of stocks in the tracking portfolio should be the minimum number of stocks needed to provide half of the capitalization of the index. However, note that none of the above-mentioned suggestions apply to our experiment because of the limitation of using US stocks only from our index (37 US stocks out of 95) or different stocks than the constituents of the benchmark index. Moreover, in the case of the physical indexes the traditional approaches do not apply as we are constrained to use a specific set of stocks to replicate a physical quantity. This can also explain the relatively low (and in some cases negative) correlations of the selected equity baskets with the BDI and BDTI (between -4.4% and 14.5%); overall, our results suggest that investors who want to participate in the physical shipping industry can still benefit from the addition of the selected baskets to a well-diversified portfolio of assets.

Finally, Table 6 presents the total number of different stocks included in the tracking baskets, throughout the entire out-of-sample period. In any case, by construction, this number cannot exceed $N = 65$ (37) for the Dow (Shipping) baskets[9]. It can be observed that the GA tends to utilize more stocks to construct the portfolios. For example the total number of stocks that the Dow DE (GA) selects to track the “Shipping” index is 19, 30 and 35 (25, 43 and 56) for annually, quarterly and monthly rebalancing (see Table 6, Panel A: K, λ = 10, 0.8). For annual portfolio revisions, both algorithms are more stable in the number of stocks picked between the various cases of the risk/return trade-off, whereas portfolios are quite different in terms of their composition when increasing the rebalancing frequency.

5. CONCLUSIONS

[9] For example, consider the annually rebalancing scheme. Starting with the first reallocation period (Feb 2008 to Feb 2009), say the algorithm selects $K = 4$ stocks, namely s_1, s_2, s_3, s_4. We count these 4 stocks. In the next period, Feb 2009 to Feb 2010, say the algorithm selects $K = 5$ stocks, namely s_1, s_2, d_1, d_2, d_3. We count only the 3 new stocks d_1, d_2 and d_3. Thus, for Feb 2008 to Feb 2010 this gives a total of 7 stocks; and so on. In the case of annually rebalancing (4 rebalancing periods) this number cannot exceed 20 when $K = 5$ and 40 for $K = 10$, i.e. at most 5 stocks per rebalancing period. Obviously, the latter reduces to 37 for the Shipping basket.

In this paper, we construct an international market-capitalisation-weighted shipping index, and its performance is reproduced by investing only in a subset of stocks within the index itself or in a subset of stocks from the Dow Jones Composite Average. We further extend our results to the case of physical shipping markets. In particular, using the Baltic Dry Index and the Baltic Dirty Tanker Index as benchmarks, we assess the tracking capability of the same set of stocks. In our methodology, we employ the differential evolution algorithm and a genetic algorithm. To test the performance of the heuristics three different rebalancing scenarios are examined: a) annually, b) quarterly and c) monthly. Transaction costs are also taken into consideration.

For the time period under investigation, and irrespective of the rebalancing frequency, the Dow GA baskets provide the minimum tracking errors and maximum mean excess returns. Although the physical shipping markets' index tracking problem provided similar results, tracking errors were much higher, mainly due to different return-risk profiles and lower correlations between the equity and physical maritime segments. Furthermore, better tracking results were obtained with a monthly rebalancing strategy. Looking at Sharpe ratios, it can be noted that annually (when tracking the BDI and BDTI) and quarterly (when tracking the shipping index) strategies perform better; this is attributed to transaction costs trimming down the returns of more frequent rebalancing strategies. Thus, it is up to the investors' risk/return preferences to decide whether rebalancing the portfolio monthly, which comes with an extra cost, is better than less frequent rebalancing. In addition, volatilities of the constructed portfolios are found to be significantly smaller for the Dow baskets, especially when tracking the BDI and BDTI. The resulting Sharpe ratios, with the exception of shipping baskets, are superior not only to the benchmark indexes but also against other widely traded benchmark financial and commodity indexes. The robustness of all results is checked by applying predictive ability tests using bootstrap simulations to determine whether any particular basket outperforms the others in terms of tracking errors and excess returns. The tests focus on the relative efficiency a) of the DE and GA algorithms employed, b) of the tracking baskets across parameters and rebalancing strategies and c) of the rebalancing scenarios.

This paper could encourage mutual and hedge fund managers to set up shipping Exchange Traded Funds (ETFs) that track our proposed shipping equity index or the two physical indexes. Similarly, investors, private and institutional, could be motivated to follow a sector of the international equity markets that deserves sole attention, which is the maritime industry. Shipping

ETFs could be utilized by ship owners, shipping market participants or other major investors to complete parts of their investment portfolios or perform tactical investment strategies. To that end, our proposed methodology puts forward an effective and at the same time least expensive way to operate such a fund.

APPENDIX

A.1 Differential Evolution Algorithm

DE is a population-based stochastic optimization algorithm that employs mutation, recombination (crossover) and selection operators to evolve iteratively an initial set (population) of NP randomly generated N-dimensional solutions. At each iteration (generation), the algorithm applies the aforementioned evolutionary operators to each one of the available solutions. In particular, let $\mathbf{x}_i^G$ denote the solution vector i ($i = 1, \dots, NP$) at a generation G, x_{ij}^G be the jth element of $\mathbf{x}_i^G$, and $\mathbf{x}_*^G$ the best solution from generation G (specified according to the problem's objective function). Having $\mathbf{x}_i^G$ as the starting basis, a new solution $\mathbf{x}_i^{G+1}$ is constructed replacing $\mathbf{x}_i^G$ in the next generation $G+1$. The solution updating process is performed in the following three steps:

1. A mutant solution $\mathbf{v}_i$ is constructed by combining $\mathbf{x}_i^G$ with $\mathbf{x}_*^G$ and two other randomly selected (different) solutions $\mathbf{x}'$ and $\mathbf{x}''$ from the current generation: $\mathbf{v}_i = \mathbf{x}_i^G + F \times (\mathbf{x}_*^G - \mathbf{x}_i^G) + F \times (\mathbf{x}' - \mathbf{x}'')$. The mutation constant $F \in (0, 2]$ controls the rate at which the population evolves.
2. The parent solution $\mathbf{x}_i^G$ and the mutant vector $\mathbf{v}_i$ are recombined to produce a crossover solution $\mathbf{u}_i$, using the exponential scheme as shown in Figure A1 (for simplicity the generation index G is not shown in the figure), where l and j^* are randomly selected from $\{1, 2, \dots, N\}$, such that the part of $\mathbf{u}_i$ derived from $\mathbf{v}_i$ is analogous to a user-defined crossover probability CR (with higher values corresponding to a stronger impact of $\mathbf{v}_i$).
3. The crossover solution $\mathbf{u}_i$ is compared against the parent vector $\mathbf{x}_{i,G}$ on the basis of the problem's objective function f. If $f(\mathbf{u}_i) \le f(\mathbf{x}_i^G)$, then $\mathbf{x}_i^{G+1}$ is set equal to $\mathbf{u}_i$ ($\mathbf{u}_i$ replaces $\mathbf{x}_{i,G}$ in the next generation); otherwise, $\mathbf{x}_i^{G+1}$ is set equal to $\mathbf{x}_i^G$.

The iterative procedure terminates when a stopping criterion is met (e.g., after a predefined number of generations is explored).

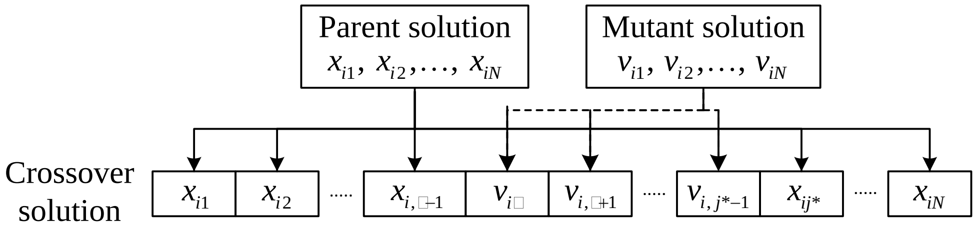

Fig. A1: DE's exponential crossover scheme.

A.2 Genetic algorithm

Similarly to the DE algorithm, a GA is also a population-based stochastic optimization process. It uses the same evolutionary operators, but implements them in a different way and does not follow the greedy approach adopted by DE. Starting with an initial (random) population of solutions, the algorithm proceeds iteratively over a number of generations. In the GA implemented in this study, the following algorithmic steps are performed at each iteration (generation):

1. A pair of parent solutions $\mathbf{x}$ and $\mathbf{y}$ is selected from the current population using a tournament selection procedure. Under this scheme, k individuals (tournament size) are randomly selected from the population with replacement, and only the best individual (according to the problem's objective function) is selected as a parent.
2. The parent solutions are used to perform the crossover operation with a pre-specified crossover probability (this probability controls the frequency with which crossover is performed). Under the arithmetic crossover scheme this operation leads to a new pair of solutions $\mathbf{x}' = r\mathbf{x} + (1-r)\mathbf{y}$ $\{\mathbf{x}', \mathbf{y}'\}$ and $\mathbf{y}' = (1-r)\mathbf{x} + r\mathbf{y}$, where r is a random number drawn from the uniform distribution in [0, 1].
3. The crossover solutions are subject to mutation. In this study the uniform mutation strategy is employed, under which $p_m N$ randomly selected elements of a solution vector are replaced by random values selected uniformly from a pre-specified range. The mutation probability p_m controls the frequency of the mutation changes.

The pair of solutions resulting from the mutation operator is placed in the next generation of solutions, and the above three steps are repeated until the new population is fully formulated. The procedure ends as soon as a termination criterion is met (e.g., the population converges or the pre-specified number of generations is reached).

Table A1

Parameters of the algorithms

GA	DE
Population size: $NP = 100$	Population size: $NP = 10N$
Generations: 100	Generations: 100
Crossover: Arithmetic (80% probability)	Mutation: Rand-to-best/1 ($F = 0.7$)
Selection: Tournament (size $= 4$)	Crossover: Exponential ($CR = 0.5$)
Mutation: Uniform (0.5% probability)	

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Table 1

Composition of the market capitalization “Shipping” index.

Rest of World Traded Stocks				USA Traded Stocks			
Company	**Sector**	**Country**	**Av.Weight/ St. Error**	**Company**	**Sector**	**Country**	**Av.Weight/ St. Error**
AP Moeller Maersk A/S	Container	Denmark	(10.0%) [0.000]	Aegean Marine Petr. Net. Inc.	Tanker	USA	(0.73%) [0.087]
Belships ASA	Dry-Bulk	Norway	(0.04%) [0.004]	Arlington Tankers Ltd.[+]	Tanker	USA	(0.29%) [0.032]
Borgestad ASA	Dry-Bulk	Norway	(0.06%) [0.003]	Baltic Trading Ltd.[•]	Dry-Bulk	USA	(0.13%) [0.018]
Brostrom AB [+]	Tanker	Sweden	(0.50%) [0.063]	Capital Product Partners LP.	Tanker	USA	(0.25%) [0.030]
China Ship. Con. Lines Co. Ltd.	Container	China	(4.79%) [0.311]	Costamare Inc.[•]	Container	USA	(0.87%) [0.081]
CSAV SA	Mixed	Chile	(1.12%) [0.096]	Danaos Corp.	Container	USA	(0.61%) [0.097]
Concordia Maritime AB	Tanker	Sweden	(0.15%) [0.020]	DHT Holdings Inc.	Tanker	USA	(0.26%) [0.028]
COSCO Shipping Co.	Mixed	China	(1.61%) [0.137]	Diana Shipping Inc.	Dry-Bulk	USA	(1.01%) [0.066]
Courage Marine Group Ltd.	Dry-Bulk	Singapore	(0.14%) [0.007]	DryShips Inc.	Mixed	USA	(1.25%) [0.137]
Eitzen Chemical ASA	Mixed	Norway	(0.28%) [0.053]	Eagle Bulk Shipping Inc.	Dry-Bulk	USA	(0.44%) [0.058]
Euronav NV	Tanker	Belgium	(1.09%) [0.105]	Euroseas Ltd.	Mixed	USA	(0.15%) [0.014]
Evergreen Marine Corp.	Container	Taiwan	(1.85%) [0.088]	Excel Maritime Carriers Ltd.	Dry-Bulk	USA	(0.37%) [0.035]
Exmar NV	Gas	Belgium	(0.63%) [0.064]	FreeSeas Inc.	Dry-Bulk	USA	(0.04%) [0.006]
Finnlines Oyj	Container	Finland	(0.57%) [0.044]	Frontline Ltd.	Tanker	USA	(2.15%) [0.200]
Globus Maritime Ltd. [+]	Dry-Bulk	UK	(0.09%) [0.018]	Genco Shipping & Trading Ltd.	Dry-Bulk	USA	(0.65%) [0.068]
Golar LNG Ltd.	Gas	Norway	(1.07%) [0.241]	General Maritime Corp. [+]	Tanker	USA	(0.58%) [0.104]
Golden Ocean Group Ltd.	Dry-Bulk	Norway	(0.55%) [0.070]	Global Ship Lease, Inc.	Container	USA	(0.13%) [0.021]
Goldenport Holdings Inc.	Mixed	UK	(0.23%) [0.028]	Knightsbridge Tankers Ltd.	Mixed	USA	(0.37%) [0.026]
Great Eastern Shipping Co.	Mixed	India	(0.91%) [0.045]	Matson, Inc.	Container	USA	(1.56%) [0.103]
Hanjin Shipping Co. Ltd.	Mixed	South Korea	(1.83%) [0.139]	Navios Maritime Holdings Inc.	Dry-Bulk	USA	(0.47%) [0.034]
Hellenic Carriers Ltd.	Dry-Bulk	UK	(0.06%) [0.010]	Navios Maritime Partners L.P.	Dry-Bulk	USA	(0.46%) [0.104]
Heung-A Shipping Co. Ltd.	Mixed	South Korea	(0.05%) [0.004]	NewLead Holdings Ltd.	Mixed	USA	(0.11%) [0.031]
Hyundai Merchant Marine Co. Ltd.	Mixed	South Korea	(3.43%) [0.166]	Nordic American Tanker Ltd.	Tanker	USA	(0.90%) [0.086]
I.M. Skaugen ASA	Mixed	Norway	(0.17%) [0.010]	OceanFreight Inc. [+]	Dry-Bulk	USA	(0.10%) [0.013]
James Fisher and Sons Plc	Tanker	UK	(0.40%) [0.019]	Overseas Ship. Group Inc.	Tanker	USA	(1.37%) [0.162]
Jinhui Shipping & Transportation Ltd.	Dry-Bulk	Norway	(0.33%) [0.036]	Paragon Shipping Inc.	Dry-Bulk	USA	(0.18%) [0.021]
Kawasaki Kisen Kaisha, Ltd.	Container	Japan	(3.36%) [0.266]	Safe Bulkers Inc.	Dry-Bulk	USA	(0.48%) [0.029]
Malaysian Bulk Carriers Berhad	Dry-Bulk	Malaysia	(0.78%) [0.038]	Scorpio Tankers Inc.[•]	Tanker	USA	(0.21%) [0.015]
Maritime Belge Compagnie SA	Dry-Bulk	Belgium	(1.20%) [0.078]	Seanergy Maritime Hldgs Corp.	Dry-Bulk	USA	(0.07%) [0.015]
MISC Berhad	Mixed	Malaysia	(8.78%) [0.038]	Seaspan Corp.	Container	USA	(0.78%) [0.043]
Mitsui O.S.K. Lines, Ltd.	Mixed	Japan	(8.37%) [0.427]	Ship Finance International Ltd.	Mixed	USA	(1.28%) [0.056]
Nanjing Tanker Corp.	Tanker	China	(1.17%) [0.128]	Star Bulk Carriers Corp.	Dry-Bulk	USA	(0.19%) [0.022]
Neptune Orient Lines Ltd.	Mixed	Singapore	(2.65%) [0.168]	Stealth Gas Inc.	Mixed	USA	(0.15%) [0.013]
Nippon Yusen Kabushiki Kaisha	Mixed	Japan	(6.84%) [0.345]	Teekay Corp.	Tanker	USA	(2.22%) [0.168]
Nordic Shipholding A/S	Tanker	Denmark	(0.06%) [0.007]	Teekay LNG Partners L.P.	Mixed	USA	(1.01%) [0.166]
Odfjell SE	Tanker	Norway	(0.67%) [0.072]	Teekay Offshore Partners L.P.	Mixed	USA	(0.69%) [0.177]
Orient Overseas (International) Ltd.	Container	Hong Kong	(3.37%) [0.258]	Teekay Tankers Ltd.	Tanker	USA	(0.25%) [0.029]
Pacific Basin Shipping Ltd.	Mixed	Hong Kong	(1.21%) [0.078]	TOP SHIPS Inc.	Mixed	USA	(0.09%) [0.023]
Pakistan National Shipping Corp.	Mixed	Pakistan	(0.09%) [0.013]	TORM A/S	Mixed	USA	(1.13%) [0.177]
Precious Shipping Ltd.	Dry-Bulk	Thailand	(0.55%) [0.022]	Tsakos Energy Navigation Ltd.	Mixed	USA	(0.68%) [0.059]
Regional Container Lines	Container	Thailand	(0.29%) [0.023]				
Rickmers Maritime	Container	Singapore	(0.14%) [0.012]				
Saga Tankers ASA	Tanker	Norway	(0.07%) [0.016]				
Samudera Shipping Line Ltd	Mixed	Singapore	(0.10%) [0.008]				
Shih Wei Navigation Co. Ltd.	Dry-bulk	Taiwan	(0.41%) [0.027]				
Shipping Corporation of India Ltd.	Mixed	India	(1.06%) [0.052]				
Sinotrans Shipping Ltd.	Mixed	Hong Kong	(1.46%) [0.103]				
Sloman Neptun Schiffahrts AG	Mixed	Germany	(0.10%) [0.006]				
SRAB Shipping [+]	Tanker	Sweden	(0.01%) [0.006]				
Stolt-Nielsen Ltd.	Mixed	Norway	(1.21%) [0.116]				
STX Pan Ocean Co. Ltd.	Mixed	South Korea	(1.78%) [0.145]				
U-Ming Marine Transport Corp.	Dry-Bulk	Taiwan	(1.45%) [0.064]				
Wilh. Wilhelmsen ASA	Container	Norway	(1.15%) [0.121]				
Wilson ASA	Mixed	Norway	(0.13%) [0.006]				
Yang Ming marine Transport Corp.	Dry-Bulk	Taiwan	(1.27%) [0.086]				

[a] The shipping basket picks up stocks trading only in the USA.

[b] Over the sample period from February 15, 2006 to February 17, 2012, the average weights (.) of the index constituents and their associated standard errors - multiplied by 10^3 [.] - are also reported.

[c] Each stock is confined to a maximum weight of 10%, and the excess weight is distributed proportionately among the remaining index constituents.

[+] denotes that company’s stock has been delisted.

[•] indicates that the stock does not qualify for the shipping basket because it has been trading for less than 2 years.

Table 2

Index tracking performance of shipping stock market

		Dow DE Basket		Dow GA Basket		Shipping DE Basket		Shipping GA Basket	
(K)	**(λ)**	**RMSE**	**ER (%)**	**RMSE**	**ER (%)**	**RMSE**	**ER (%)**	**RMSE**	**ER (%)**
Panel A: Annually Rebalancing									
5	0.6	0.01580	0.0468	0.01549	0.0528	0.01612	-0.0258	0.01575	-0.0227
	0.8	0.01559	0.0508	0.01540	0.0784	0.01561	-0.0237	0.01549	-0.0007
	1	0.01559	0.0489	0.01548	0.0678	0.01565	-0.0208	0.01569	-0.0318
10	0.6	0.01522	0.0517	0.01535	0.0549	0.01587	-0.0402	0.01549	-0.0281
	0.8	0.01538	0.0485	0.01523	0.0553	0.01573	-0.0411	0.01541	-0.0428
	1	0.01534	0.0494	0.01513[a]	0.0431	0.01550	-0.0433	0.01494[a]	-0.0307
Panel B: Quarterly Rebalancing									
5	0.6	0.01559	0.0424	0.01530	0.0819	0.01567	-0.0180	0.01527[a]	-0.0349
	0.8	0.01569	0.0431	0.01511[a]	0.0573	0.01560	-0.0289	0.01480[a]	-0.0350
	1	0.01567	0.0454	0.01517[a]	0.0327	0.01564	-0.0282	0.01544[a]	-0.0474
10	0.6	0.01534	0.0467	0.01492[a]	0.0579	0.01529	-0.0444	0.01501	-0.0281
	0.8	0.01537	0.0364	0.01487[a]	0.0506	0.01525	-0.0547	0.01486[a]	-0.0247
	1	0.01544	0.0328	0.01506[a]	0.0242	0.01534	-0.0585	0.01503[a]	-0.0632
Panel C: Monthly Rebalancing									
5	0.6	0.01564	0.0237	**0.01482**[a]	**0.0751**	0.01567	-0.0494	0.01451[a]	-0.0099
	0.8	0.01562	0.0212	0.01459[a]	0.0565	0.01567	-0.0607	0.01445[a]	-0.0539
	1	0.01559	0.0237	0.01447[a]	0.0309	0.01573	-0.0680	0.01481[a]	-0.0936
10	0.6	0.01543	0.0237	0.01492[a]	0.0625	0.01509	-0.0690	0.01416[a]	-0.0395
	0.8	0.01539	0.0153	0.01476[a]	0.0168	0.01509	-0.0735	0.01423[a]	-0.0544
	1	0.01536	0.0114	0.01487[a]	0.0162	0.01504	-0.0796	0.01443[a]	-0.0787

[a] The sample spans from February 15, 2006 to February 17, 2012. The first two years are used as the estimation period whereas the remaining four years is our test period. Our tracking portfolios include stocks picked each time from the Dow and Shipping (US constituents only) indexes, which contain N = 65 and 37 stocks, respectively.

[b] RMSE and ER (%) stand for Root Mean Squared Errors and mean daily percentage Excess Returns, as defined in equations (1) and (2), respectively. Numbers in bold indicate the strategy that the objective function of equation (3) is minimized.

[c] Panels A, B and C report the results under three rebalancing schemes, annually, quarterly and monthly, respectively; for example, under monthly rebalancing the weights of the tracking portfolios are estimated, based on the available data in the rolling in-sample estimation window (two years), every month.

[d] Portfolio returns are adjusted for transaction costs of 0.75% for each transaction.

[e] The tracking portfolios are created based on the stocks that the Differential Evolution (DE) and Genetic Algorithms (GA) choose. To decide which stocks will be included in the tracking portfolio, we use two main objectives, the tracking error and the excess return.

[f] K is the maximum number of stocks allowed to be included in the selected baskets, and λ is the generalized minimization objective for the index tracking problem; in the case that λ takes the value of 1, the tracking portfolio's main objective is to minimize the tracking error, whereas, when λ equals 0, the portfolio's main goal is to maximize the excess return.

[g] We also perform Hansen's (2005) test of Superior Predictive Ability (SPA test) using 5,000 bootstrap simulations (Politis & Romano, 2004 stationary bootstrap) and q=0.25 to test whether there are any significant differences among the RMSEs and ERs of the tracking portfolios: Superscript a tests the efficiency of the two algorithms and denotes the case when a particular algorithm outperforms the competing algorithm (pairwise comparison) corresponding to the same basket, e.g. Dow DE vs. Dow GA. Superscript b denotes the case when a particular basket outperforms consistently the rival baskets (comparison in rows), e.g. Dow DE vs. Dow GA, Shipping DE and Shipping GA (joint test). For the purposes of presentation the significance level considered is 5%.

Table 3

Index tracking performance of the shipping physical market

		Dow DE Basket		Dow GA Basket		Shipping DE Basket		Shipping GA Basket	
(K)	(λ)	RMSE	ER (%)	RMSE	ER (%)	RMSE	ER (%)	RMSE	ER (%)
Panel A: Baltic Dry Index									
				Annually Rebalancing					
5	0.6	0.03027	0.2414	0.03008[a, b]	0.2531	0.03558	0.1747	0.03504[a]	0.2138
	0.8	0.03027	0.2412	0.02994[a, b]	0.2396	0.03542	0.1766	0.03537	0.1837
	1	0.03025	0.2434	0.03009[a, b]	0.2415	0.03546	0.1765	0.03510[a]	0.1863
10	0.6	0.03031	0.2381	0.02999[a, b]	0.2361	0.03561	0.1641	0.03468[a]	0.1733
	0.8	0.03030	0.2384	0.03015[a, b]	0.2423	0.03550	0.1647	0.03485[a]	0.1707
	1	0.03028	0.2387	0.02998[a, b]	0.2451	0.03551	0.1627	0.03515[a]	0.1550
				Quarterly Rebalancing					
5	0.6	0.03030	0.2325	0.02966[a, b]	0.2323	0.03592	0.1553	0.03499[a]	0.1673
	0.8	0.03023	0.2321	0.02963[a, b]	0.2288	0.03604	0.1516	0.03473[a]	0.1328
	1	0.03022	0.2313	0.02966[a, b]	0.2227	0.03601	0.1398	0.03504[a]	0.1164
10	0.6	0.03024	0.2260	0.02960[a, b]	0.2265	0.03580	0.1387	0.03464[a]	0.1536
	0.8	0.03026	0.2279	0.02978[a, b]	0.2317	0.03598	0.1324	0.03491[a]	0.1358
	1	0.03028	0.2292	0.02958[a, b]	0.2290	0.03613	0.1300	0.03462[a]	0.1266
				Monthly Rebalancing					
5	0.6	0.03022	0.2046	**0.02940[a, b]**	**0.2285**	0.03525	0.1168	0.03382[a]	0.1599
	0.8	0.03024	0.2024	0.02953[a, b]	0.2082	0.03530	0.1107	0.03381[a]	0.1421
	1	0.03028	0.2026	0.02941[a, b]	0.1958	0.03537	0.1006	0.03405[a]	0.0895
10	0.6	0.03021	0.2007	0.02941[a, b]	0.2261	0.03523	0.1042	0.03415[a]	0.1419
	0.8	0.03028	0.2003	0.02943[a, b]	0.2181	0.03538	0.0953	0.03399[a]	0.0989
	1	0.03031	0.2001	0.02938[a, b]	0.2046	0.03551	0.0921	0.03403[a]	0.0969
Panel B: Baltic Dirty Tanker Index									
				Annually Rebalancing					
5	0.6	0.02855	0.0657	0.02774[a, b]	0.0856	0.03285	0.0104	0.03283	0.0286
	0.8	0.02858	0.0643	0.02783[a, b]	0.0623	0.03320	0.0088	0.03276[a]	0.0130
	1	0.02860	0.0632	0.02795[a, b]	0.0660	0.03315	0.0092	0.03253	0.0139
10	0.6	0.02858	0.0618	0.02814[a, b]	0.0717	0.03311	-0.0004	0.03265[a]	0.0097
	0.8	0.02859	0.0605	0.02808[a, b]	0.0790	0.03302	0.0016	0.03285	0.0012
	1	0.02867	0.0562	0.02802[a, b]	0.0581	0.03301	0.0004	0.03266[a]	0.0064
				Quarterly Rebalancing					
5	0.6	0.02819	0.0504	0.02750[a, b]	0.0605	0.03298	-0.0150	0.03197[a]	0.0323
	0.8	0.02836	0.0473	0.02752[a, b]	0.0637	0.03326	-0.0218	0.03216[a]	-0.0037
	1	0.02851	0.0451	0.02780[a, b]	0.0526	0.03323	-0.0188	0.03189[a]	-0.0148
10	0.6	0.02821	0.0460	0.02758[a, b]	0.0586	0.03277	-0.0182	0.03186[a]	-0.0079
	0.8	0.02837	0.0459	0.02762[a, b]	0.0502	0.03295	-0.0239	0.03238[a]	-0.0099
	1	0.02849	0.0435	0.02772[a, b]	0.0555	0.03313	-0.0298	0.03235[a]	-0.0520
				Monthly Rebalancing					
5	0.6	0.02815	0.0202	**0.02724[a, b]**	**0.0594**	0.03229	-0.0475	0.03107[a]	0.0263
	0.8	0.02820	0.0174	0.02738[a, b]	0.0465	0.03239	-0.0559	0.03115[a]	-0.0537
	1	0.02832	0.0146	0.02733[a, b]	0.0371	0.03268	-0.0557	0.03139[a]	-0.0722
10	0.6	0.02816	0.0165	0.02736[a, b]	0.0687	0.03231	-0.0508	0.03170[a]	-0.0063
	0.8	0.02824	0.0167	0.02722[a, b]	0.0392	0.03245	-0.0600	0.03113[a]	-0.0437
	1	0.02834	0.0163	0.02746[a, b]	0.0340	0.03260	-0.0654	0.03118[a]	-0.0756

[a] See Notes in Table 2.

Table 4

Statistics of the shipping stock market tracking portfolios

		Dow DE basket				Dow GA basket				Shipping DE basket				Shipping GA basket			
(K)	**(λ)**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**
Panel A: Annually Rebalancing																	
5	0.6	0.74	25.10	54.27	**0.029**	2.26	22.88	52.94	**0.099**	-17.56	35.39	69.46	-0.496	-16.77	34.46	69.42	-0.487
	0.8	1.74	25.34	55.83	**0.069**	8.72	23.56	54.46	**0.370**	-17.01	34.04	69.36	-0.500	-11.24	33.65	69.21	**-0.334**
	1	1.28	25.31	55.77	**0.051**	6.04	24.55	55.35	**0.246**	-16.29	34.12	69.29	-0.477	-19.06	34.20	69.25	-0.557
10	0.6	1.98	24.25	56.44	**0.082**	2.79	23.60	54.80	**0.118**	-21.18	36.62	72.57	-0.578	-18.13	35.04	71.48	-0.517
	0.8	1.17	24.56	55.88	**0.048**	2.90	24.83	57.18	**0.117**	-21.42	36.14	72.35	-0.593	-21.82	35.28	72.20	-0.618
	1	1.40	24.51	56.06	**0.057**	-0.19	24.37	57.06	**-0.008**	-21.97	35.46	72.14	-0.620	-18.79	33.95	71.98	-0.553
Panel B: Quarterly Rebalancing																	
5	0.6	-0.36	24.94	55.22	**-0.014**	9.58	23.13	54.53	**0.414**	-15.59	33.98	68.99	-0.459	-19.84	33.53	69.98	-0.592
	0.8	-0.19	25.29	55.14	**-0.008**	3.38	24.01	56.78	**0.141**	-18.34	33.76	68.90	-0.543	-19.88	33.07	71.20	-0.601
	1	0.40	25.42	55.45	**0.016**	-2.82	23.58	55.79	**-0.120**	-18.15	33.88	68.96	-0.536	-23.01	33.76	69.62	-0.682
10	0.6	0.72	24.68	56.32	**0.029**	3.53	23.17	56.78	**0.152**	-22.23	34.84	72.00	-0.638	-18.12	34.16	72.04	-0.530
	0.8	-1.88	25.07	56.64	**-0.075**	1.70	24.58	58.86	**0.069**	-24.83	34.84	72.16	-0.713	-17.29	33.96	72.34	-0.509
	1	-2.79	25.16	56.36	**-0.111**	-4.94	24.52	57.66	**-0.201**	-25.79	34.97	72.02	-0.737	-26.98	34.50	72.53	-0.782
Panel C: Monthly Rebalancing																	
5	0.6	-5.07	24.70	54.57	**-0.205**	7.88	23.79	58.21	**0.331**	-23.49	33.70	68.55	-0.697	-13.55	33.04	72.34	-0.410
	0.8	-5.70	24.98	55.06	**-0.228**	3.18	23.15	58.74	**0.137**	-26.35	33.78	68.68	-0.780	-24.63	32.85	72.33	-0.750
	1	-5.08	25.27	55.68	**-0.201**	-3.26	23.52	59.78	**-0.139**	-28.18	33.88	68.63	-0.832	-34.63	33.92	72.57	-1.021
10	0.6	-5.08	24.66	55.73	**-0.206**	4.71	22.66	56.20	**0.208**	-28.43	34.14	71.72	-0.833	-20.99	32.97	73.68	-0.637
	0.8	-7.19	25.02	56.46	-0.287	-6.81	23.92	58.62	**-0.285**	-29.56	34.17	71.80	-0.865	-24.76	33.53	74.24	-0.738
	1	-8.19	25.25	56.94	-0.324	-6.97	23.93	57.96	-0.291	-31.12	34.19	72.02	-0.910	-30.89	33.87	74.00	-0.912

Panel D: Return/Risk of Shipping and other Indexes

	Ann Ret	Ann Vol	Sharpe R
Shipping Index	-11.05	27.20	-0.406
Baltic Dry Index	-57.01	43.28	-1.317
Baltic Dirty Tanker Index	-11.80	41.29	-0.286
Dow Jones Composite	0.88	26.49	0.033
S&P 500	0.02	28.50	0.001
NASDAQ 100	9.22	29.01	0.318
Dow Jones – UBS Commodity Index	-8.92	23.05	-0.387

[a] Ann Ret and Ann Vol are the annualized mean returns and annualized volatilities of the tracking portfolios, assuming 252 trading days in each calendar year.
[b] Correl is the correlation coefficient between the returns of the benchmark index and the tracking portfolio.
[c] Sharpe R denotes the Sharpe Ratio, calculated using the formula Ann Ret / Ann Vol. Figures in bold signify that the excess Sharpe R, compared to the benchmark index Sharpe R, is positive. Underlined figures indicate the best performing strategies.
[d] All figures are in % terms.
[e] For further details, see notes in Table 2.

Table 5

Statistics of the shipping physical market tracking portfolios.

		Dow DE basket				Dow GA basket				Shipping DE basket				Shipping GA basket			
(K)	**(λ)**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**	**Ann Ret**	**Ann Vol**	**Correl**	**Sharpe R**
Panel A: Baltic Dry Index																	
								Annually Rebalancing									
5	0.6	3.81	19.06	-3.65	**0.200**	6.76	18.95	-2.01	**<u>0.357</u>**	-12.98	35.26	-2.27	**-0.368**	-3.13	33.37	-3.40	**-0.094**
	0.8	3.76	19.01	-3.79	**0.198**	3.37	18.51	-1.90	**0.182**	-12.50	34.35	-3.49	**-0.364**	-10.71	34.02	-3.99	**-0.315**
	1	4.32	18.68	-4.42	**0.231**	3.84	19.14	-1.81	**0.201**	-12.53	34.38	-3.63	**-0.364**	-10.07	33.48	-3.60	**-0.301**
10	0.6	2.98	19.12	-3.86	**0.156**	2.47	18.98	-1.31	**0.130**	-15.66	35.56	-1.75	**-0.440**	-13.34	33.12	-1.95	**-0.403**
	0.8	3.07	19.05	-3.92	**0.161**	4.05	18.57	-3.74	**0.218**	-15.52	34.92	-2.65	**-0.444**	-14.00	33.60	-1.84	**-0.417**
	1	3.13	19.01	-3.88	**0.165**	4.74	18.29	-2.88	**0.259**	-16.03	34.79	-2.98	**-0.461**	-17.96	34.76	-0.93	**-0.517**
								Quarterly Rebalancing									
5	0.6	1.58	19.22	-3.53	**0.082**	1.51	18.17	-0.12	**0.083**	-17.88	35.81	-3.00	**-0.499**	-14.85	33.88	-2.07	**-0.438**
	0.8	1.47	19.16	-3.03	**0.077**	0.64	17.98	-0.33	**0.036**	-18.80	35.93	-3.43	**-0.523**	-23.56	33.33	-1.87	**-0.707**
	1	1.27	19.03	-3.41	**0.067**	-0.90	18.08	-0.45	**-0.050**	-21.77	35.87	-3.44	**-0.607**	-27.68	34.21	-1.68	**-0.809**
10	0.6	-0.05	19.08	-3.44	**-0.003**	0.05	18.04	0.11	**0.003**	-22.05	35.58	-2.88	**-0.620**	-18.31	33.46	-0.94	**-0.547**
	0.8	0.41	19.13	-3.48	**0.021**	1.37	18.27	-1.02	**0.075**	-23.65	35.81	-3.40	**-0.660**	-22.80	34.03	-1.28	**-0.670**
	1	0.75	19.17	-3.53	**0.039**	0.69	18.36	1.03	**0.038**	-24.26	36.18	-3.42	**-0.671**	-25.12	33.65	-0.49	**-0.747**
								Monthly Rebalancing									
5	0.6	-5.44	19.13	-3.26	**-0.284**	0.58	18.32	2.62	**0.032**	-27.58	34.10	-3.22	**-0.809**	-16.71	32.23	1.16	**-0.518**
	0.8	-6.01	19.15	-3.38	**-0.314**	-4.55	18.46	1.55	**-0.246**	-29.11	34.22	-3.21	**-0.851**	-21.21	32.26	1.29	**-0.657**
	1	-5.97	19.17	-3.71	**-0.311**	-7.68	18.47	2.65	**-0.416**	-31.66	34.45	-3.14	**-0.919**	-34.45	33.01	1.41	**-1.044**
10	0.6	-6.43	19.08	-3.35	**-0.337**	-0.03	17.75	1.23	**-0.002**	-30.75	34.37	-2.46	**-0.895**	-21.25	32.75	0.33	**-0.649**
	0.8	-6.55	19.22	-3.64	**-0.341**	-2.05	18.22	2.11	**-0.113**	-33.00	34.67	-2.66	**-0.952**	-32.08	32.89	1.51	**-0.975**
	1	-6.60	19.31	-3.67	**-0.342**	-5.44	18.40	2.87	**-0.296**	-33.81	34.98	-2.69	**-0.967**	-32.60	32.75	0.96	**-0.995**
Panel B: Baltic Dirty Tanker Index																	
								Annually Rebalancing									
5	0.6	4.75	21.03	5.27	**0.226**	9.76	18.26	6.56	**<u>0.535</u>**	-9.18	34.56	6.24	**-0.266**	-4.59	34.98	7.27	**-0.131**
	0.8	4.42	20.98	4.97	**0.211**	3.89	18.60	6.41	**0.209**	-9.58	35.84	7.07	**-0.267**	-8.52	34.93	7.57	**-0.244**
	1	4.12	21.05	4.91	**0.196**	4.83	18.90	5.96	**0.256**	-9.48	35.72	7.09	**-0.265**	-8.30	33.89	6.58	**-0.245**
10	0.6	3.77	21.11	5.20	**0.179**	6.27	19.50	5.57	**0.322**	-11.91	35.40	6.61	-0.336	-9.36	34.52	7.27	**-0.271**
	0.8	3.45	20.97	4.88	**0.165**	8.10	19.23	5.48	**0.421**	-11.38	35.25	6.79	-0.323	-11.48	35.16	7.55	-0.327
	1	2.36	21.21	4.69	**0.111**	2.85	18.74	4.92	**0.152**	-11.70	35.25	6.85	-0.332	-10.18	34.98	8.25	-0.291
								Quarterly Rebalancing									
5	0.6	0.91	20.09	6.31	**0.045**	3.44	18.91	9.94	**0.182**	-15.58	35.48	7.51	-0.439	-3.67	33.71	9.48	**-0.109**
	0.8	0.13	20.39	5.50	**0.006**	4.26	18.63	9.28	**0.229**	-17.28	35.89	6.85	-0.481	-12.73	34.85	10.8	-0.365
	1	-0.43	20.71	4.87	**-0.021**	1.45	18.81	7.05	**0.077**	-16.54	35.67	6.54	-0.464	-15.53	33.48	9.40	-0.464
10	0.6	-0.20	20.19	6.31	**-0.010**	2.98	18.77	9.00	**0.159**	-16.39	34.91	7.45	-0.469	-13.79	34.13	11.0	-0.404
	0.8	-0.22	20.44	5.53	**-0.011**	0.86	18.54	8.18	**0.046**	-17.83	35.29	7.25	-0.505	-14.28	34.78	9.40	-0.411
	1	-0.84	20.63	4.93	**-0.041**	2.20	19.37	8.91	**0.114**	-19.31	35.64	7.00	-0.542	-24.90	34.81	9.66	-0.715
								Monthly Rebalancing									
5	0.6	-6.71	19.82	6.08	-0.339	3.17	18.51	11.57	**0.171**	-23.77	33.98	8.22	-0.700	-5.16	33.66	14.52	**-0.153**
	0.8	-7.41	19.95	5.91	-0.371	-0.07	18.71	10.63	**-0.004**	-25.88	34.42	8.57	-0.752	-25.33	32.71	12.15	-0.774
	1	-8.13	20.09	5.13	-0.405	-2.44	18.59	10.90	**-0.131**	-25.83	34.71	7.58	-0.744	-29.99	33.24	11.86	-0.902
10	0.6	-7.64	19.88	6.13	-0.384	5.52	18.99	11.35	**0.291**	-24.61	33.99	8.12	-0.724	-13.38	33.43	10.41	-0.400
	0.8	-7.58	19.96	5.60	-0.380	-1.92	18.68	11.99	**-0.103**	-26.92	34.30	7.99	-0.785	-22.82	32.26	11.31	-0.707
	1	-7.68	20.17	5.15	-0.381	-3.23	19.16	10.76	**-0.169**	-28.29	34.68	7.96	-0.816	-30.84	32.87	12.35	-0.938

[a] See Notes in Table 4.

Table 6

Number of stocks included in the tracking portfolios

		Dow DE Basket			Dow GA Basket			Shipping DE Basket			Shipping GA Basket		
(K)	**(λ)**	**A**	**Q**	**M**	**A**	**Q**	**M**	**A**	**Q**	**M**	**A**	**Q**	**M**
Panel A: Shipping Index													
5	0.6	11	18	20	14	28	45	7	12	15	11	19	27
	0.8	11	17	21	14	30	47	6	12	15	10	17	23
	1	11	19	26	12	37	46	7	11	15	10	18	26
10	0.6	16	24	31	19	42	53	18	27	29	17	30	34
	0.8	19	30	35	25	43	56	18	25	27	20	29	36
	1	19	32	40	21	41	54	19	23	26	17	31	35
Panel B: Baltic Dry Index													
5	0.6	10	14	14	8	13	23	10	18	18	8	18	25
	0.8	10	12	12	7	11	22	9	18	19	10	19	25
	1	10	13	14	6	12	23	9	18	20	8	21	30
10	0.6	15	20	27	10	18	28	17	27	27	14	25	33
	0.8	15	20	21	12	18	29	17	27	29	14	30	30
	1	15	19	20	6	15	32	17	28	29	18	24	34
Panel C: Baltic Dirty Tanker Index													
5	0.6	11	14	16	6	23	33	9	15	18	9	14	20
	0.8	11	15	17	13	21	30	10	17	17	9	15	22
	1	11	15	19	8	17	32	10	18	20	9	13	22
10	0.6	18	27	29	11	22	38	14	23	26	12	20	29
	0.8	18	24	26	14	25	37	17	22	25	13	24	28
	1	18	26	26	10	23	38	16	23	25	14	24	29

[a] Columns "A", "Q" and "M" denote the Annually, Quarterly and Monthly rebalancing schemes and display the total number of stocks selected in each tracking portfolio, respectively.

[b] For further details, see also Table 2.

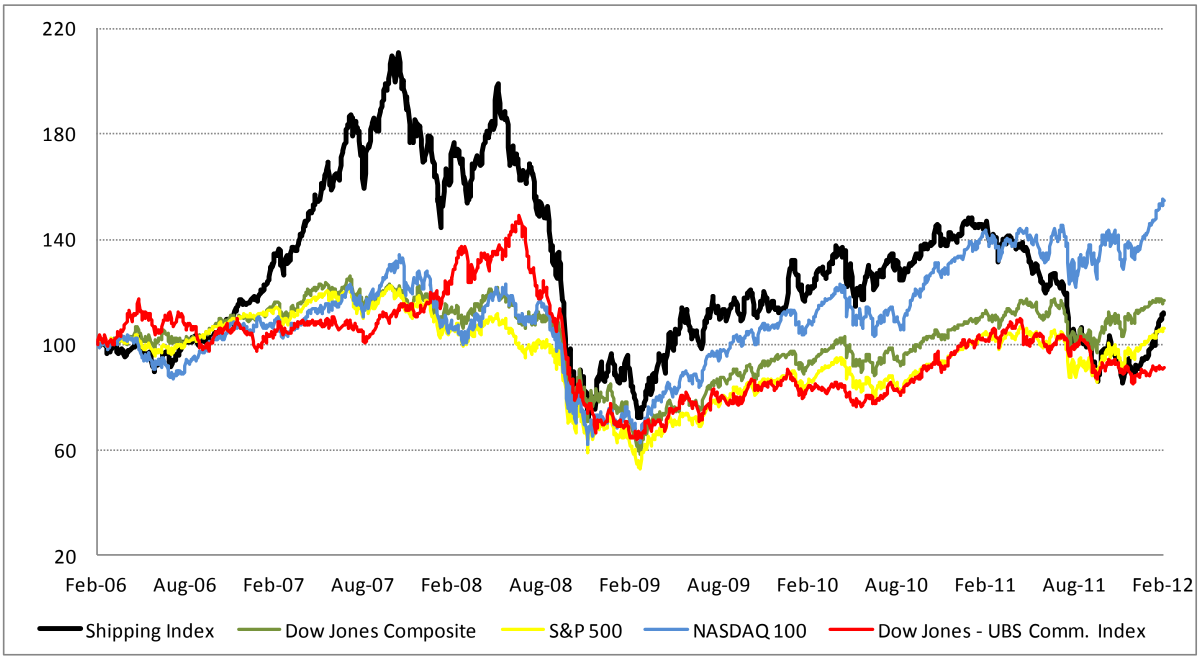

Fig. 1. Relative Performance of the "Shipping" Index vs. Financial and Commodity Indexes.

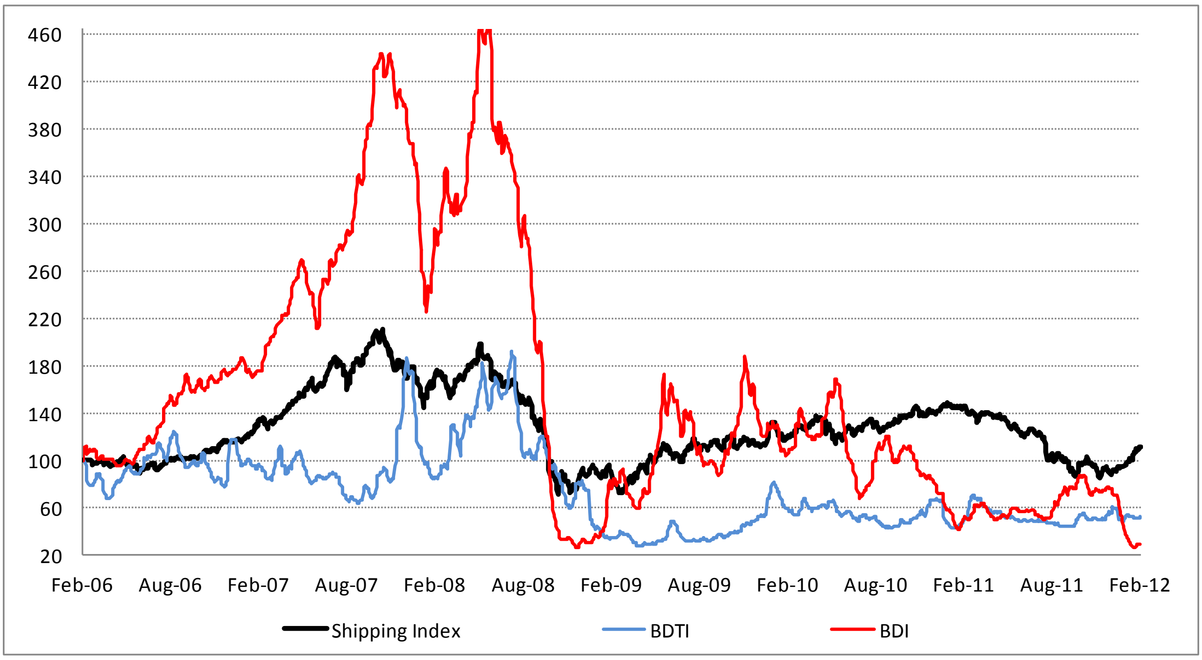

Fig. 2. Relative Performance of BDI and BDTI vs. the "Shipping" Index.

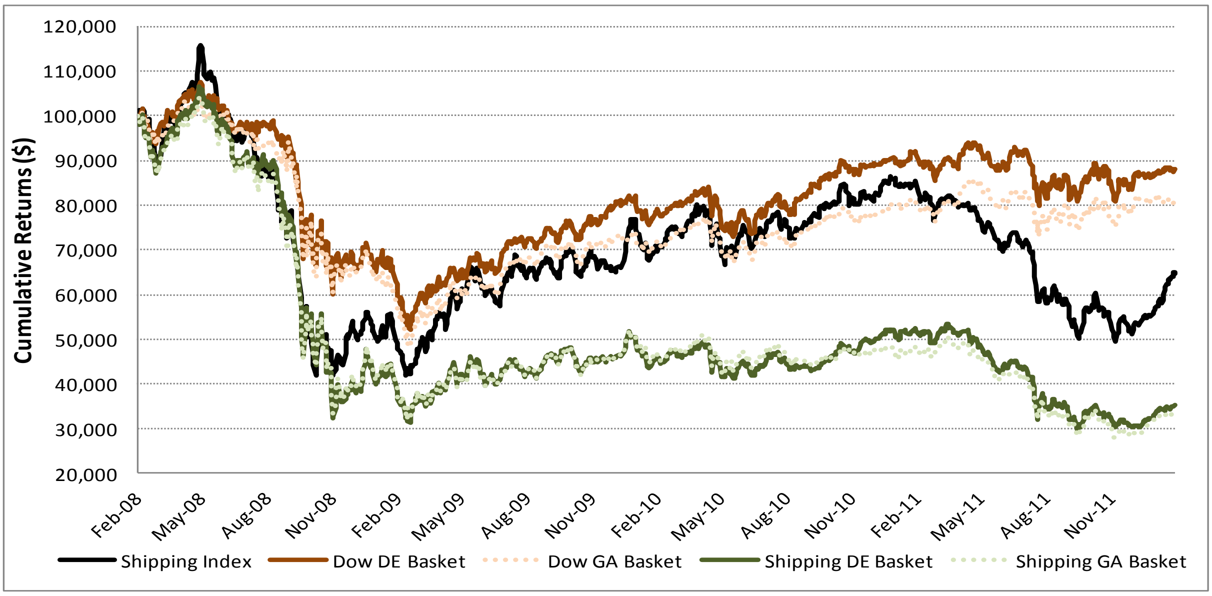

Fig. 3. Out-of-Sample cumulative returns of the "Shipping" index vs. the Dow and Shipping tracking portfolios with (K, λ) = (10, 1); stocks in the baskets are rebalanced quarterly.

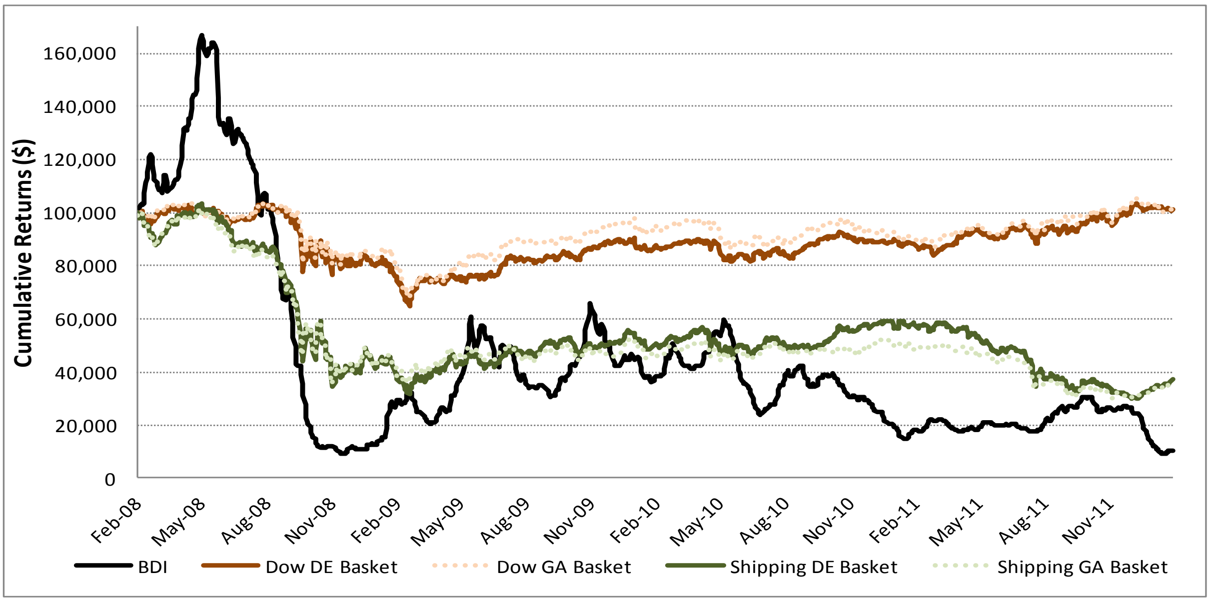

Fig. 4. Out-of-Sample cumulative returns of the BDI index vs. the Dow and Shipping tracking portfolios with (K, λ) = (10, 1); stocks in the baskets are rebalanced quarterly.

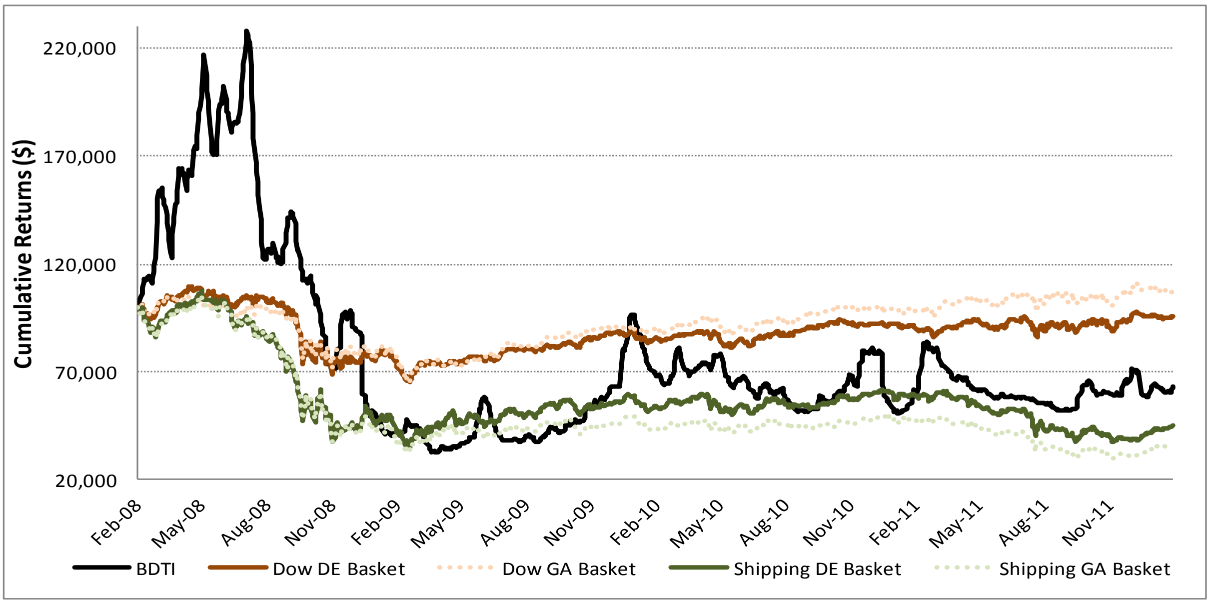

Fig. 5. Out-of-Sample cumulative returns of the BDTI index vs. the Dow and Shipping tracking portfolios with (K, λ) = (10, 1); stocks in the baskets are rebalanced quarterly.