Working Paper No 04/00

Technical trading rule performance in the second-hand asset markets in bulk shipping

by

Roar Os Ådland

SNF project no 1055

The project is financed by the Norwegian Shipowners Association

SIØS - Centre for International Economics and Shipping

FOUNDATION FOR RESEARCH IN ECONOMICS AND BUSINESS ADMINISTRATION

BERGEN, JANUARY 2000

ISSN 0803 - 4028

SIØS – Centre for international economics and shipping – is a joint centre for The Norwegian School of Economics and Business Administration (NHH) and The Foundation for Research in Economics and Business Administration (SNF). The centre is responsible for research and teaching within the fields of international trade and shipping.

International Trade
The centre works with all types of issues related to international trade and shipping, and has particular expertise in the areas of international real economics (trade, factor mobility, economic integration and industrial policy), international macro economics and international tax policy. Research at the centre has in general been dominated by projects aiming to provide increased insight into global, structural issues and the effect of regional economic integration. However, the researchers at the centre also participate actively in projects relating to public economics, industrial policy and competition policy.

International Transport
International transport is another central area of research at the centre. Within this field, studies of the competition between different modes of transport in Europe and the possibilities of increasing sea transport with a view to easing the pressure on the land based transport network on the Continent have been central.

Maritime Research
One of the main tasks of the centre is to act as a link between the maritime industry and the research environment at SNF and NHH. A series of projects that are financed by the Norwegian Shipowners Association and aimed directly at shipowning firms and other maritime companies have been conducted at the centre. These projects include studies of Norwegian shipowners' multinational activities, shipbuilding in Northern Europe and the competition in the ferry markets.

Human Resources
The centre's human resources include researchers at SNF and affiliated professors at NHH as well as leading international economists who are affiliated to the centre through long-term relations. During the last few years the centre has produced five PhDs within international economics and shipping.

Networks
The centre is involved in several major EU projects and collaborates with central research and educational institutions all over Europe. There is particularly close contact with London School of Economics, University of Glasgow, The Graduate Institute of International Studies in Geneva and The Research Institute of Industrial Economics (IUI) in Stockholm. The staff members participate in international research networks, including Centre for Economic Policy Research (CEPR), London, International Association of Maritime Economists (IAME).

Technical trading rule performance in the second-hand asset markets in bulk shipping

By Roar Os Ådland
Norwegian School of Economics and Business Administration (NHH)
and
Massachusetts Institute of Technology
Email: roaaad@mit.edu

Non-technical Summary

This paper investigates the performance of technical trading rules applied to asset play in the international bulk shipping industry. The rules are tested on monthly returns in the Products Carrier segment for the period 1981 to 1998. The paper evaluates 1053 different parameterizations of three of the simplest and most popular trading rules in the financial markets: filter rules, moving averages, and support and resistance levels. Overall, the results provide strong support for the technical strategies. None of the trading rules generate negative cumulative wealth, and only one parameterization results in a mean return that is lower than the return from the benchmark buy-and-hold strategy. The results for the best-performing trading rule show that the mean return following buy signals is positive and the mean return following sell signals is negative, both significantly different from the buy-and-hold mean return according to standard statistical tests. Moreover, the returns following buy signals are less volatile than those following sell signals, as well as the returns of the buy-and-hold strategy. The best-performing trading rule obtains a mean return of 35.4% p.a. above the buy-and-hold annual return of 4.0%. Due to a low number of trades, the introduction of trading costs has little impact on the results. Adjusting for data-snooping biases according to White's Reality Check bootstrap methodology confirms the conclusion that the best-performing trading rule provides superior investing performance. However, the practical implementation in an illiquid market may reduce the

theoretical excess return of the best-performing trading rule to a level where it is no longer significant. Moreover, the probability that an investor could have picked ex ante a trading rule with statistically significant excess return is small.

1 Introduction

Technical analysis is a generic term that includes many different techniques with the goal of predicting the future evolution of asset prices from the observation of past prices. These techniques are considered by many to be the original form of investment analysis dating back to the writings of Wall Street Journal editor Charles Dow in the 1800s, long before modern financial theory was born. Most of the time, technical analysis has been looked at with contempt by academics. The main reason is that technical analysis violates the efficient market hypothesis which holds that it is impossible to predict future prices from the observation of past prices. Furthermore, early tests of the profitability of technical trading rules produced very poor results, which reinforced the negative attitude in academia towards such analysis. However, practitioners are still using these techniques to make investment decisions. Over the last decade, a number of empirical studies have produced results on the predictability of asset prices that seemingly contradict the efficient market hypothesis, and, over the same time period, there has been a renewed interest in technical analysis also from an academic point of view. By and large, recent academic literature suggests that technical trading rules are capable of producing valuable economic signals. The results are in sharp contrast with most of the earlier studies that supported the random walk hypothesis and concluded that the predictable variation in returns was economically and statistically very small. Two competing explanations for the presence of predictable variation in asset prices have been suggested: (1) the markets are not efficient even in the weak form, or (2) markets are efficient and the predictable variation can be explained by time-varying risk premia.

This paper is in line with recent literature on technical trading rules which tests whether such rules are profitable when the results are adjusted for transaction costs and the potential effect of data snooping. However, the analysis concerns an area that is rarely investigated in academia, namely asset values in the international bulk shipping markets. Despite the intriguing qualities of these markets, such as large long-run price swings exhibiting a clear mean reverting pattern, there have been no recent attempts to investigate the merits of "value play" models in this context. The reason, aside from being a less-known market, may be that financial markets dealing in stocks and foreign exchange provide easily accessible and long time series of standardized high-frequency data, while the shipping markets do not. Also, most practitioners regard technical analysis as a short-horizon trading method, with positions in the stock, commodity or foreign exchange markets lasting a few hours or days. When an investor buys a ship, the transaction itself may take several weeks. However, there are indications that, in a cyclical market such as bulk shipping, technical analysis may be a tool to uncover market turns. Vessel values may not always be determined by economic fundamentals like freight rates, but rather driven away from fundamental values by shipowners' irrational expectations of future freight rates. Returns in the second-hand market for ships typically exhibit the characteristics that Cutler, Poterba and Summers (1990) suggest are typical to speculative dynamics: (1) returns display positive autocorrelations at relative short horizons, (2) returns are negatively autocorrelated at durations of several years, and (3) returns over periods of several years can be predicted on the basis of crude proxies for the deviation of asset prices from fundamental value. A proxy for the fundamental value in this case could be a constant multiple of earnings. Stopford (1997) estimates that when freight rates are high, the S & P market values a five-year old ship at about ten times its current annual earnings. In recessions, the value may fall as low as three times annual earnings. This paper investigates the merits of technical analysis in bulk shipping asset play.

The plan of the paper is as follows. Section 1 reviews the existing evidence on technical trading rules, section 2 describes the problem of data snooping and its remedies, and section 3 describes the data used in this paper. Section 4 describes the technical trading rules and the theoretical methodology behind the results. Section 5 presents the empirical results, and, finally, section 6 contains the conclusion and discusses the economic interpretation of the findings.

2 Previous research

Technical trading rules investigated in academic literature can be divided in two major areas: filter rules and moving average rules. Early research, such as Alexander (1961 and 1964) focused on filter rules to assess the efficiency of stock price movements. In his first article Alexander found the filter rules to be profitable. However, after he included transaction costs in his second article, the profits generated by these strategies vanished. Fama and Blume (1966) confirmed this conclusion and this led the academic community to be skeptical about technical analysis not only because it lacked theoretical foundation but also because it yielded poor results. Sweeney (1988) re-examined the results of Fama and Blume for a subsequent time period and found that, depending on the level of transaction costs, filter rules still yielded profitable results.

In the early nineties, the research focused on moving average crossover rules, which are some of the most popular and common trading rules discussed in the technical analysis literature. Brock, Lakonishok and LeBaron (BLL 1992) investigated moving average rules on daily data of the Dow Jones Industrial Index from 1897 to 1986 and concluded that the buy and sell signals generated by these rules were able to detect "abnormal" returns. By using bootstrap tests, BLL showed that the results were robust to other specifications of the return generating process. However, BLL ignored trading costs. Furthermore, Sullivan, Timmerman and White (STW 1998) show that BLLs "best" trading rule did not outperform the buy-and-hold benchmark at conventional levels of significance in the ten-year period that followed. Hudson, Dempsey and Keasey (1996), who replicate the Brock et al's tests on the UK stock market for the period 1935 to 1994, found that any profitable results vanished when trading costs were considered. Isakov and Hollistein (1997) confirm the same result in Swiss stock prices for the period 1969 to 1997. Levich and Thomas (1993) and Kho (1996) found some profitable results with the moving average strategies in the foreign exchange futures markets, even after accounting for transaction costs. Kho showed that these results were partly due to a time-varying risk premia. Evidence in favor of technical analysis is also reported in Osler and Chang (1995) who use bootstrap procedures to examine charting pattern in foreign exchange markets.

The only previous research paper I have come across that attempts to use technical trading rules on second-hand vessel values is Norman (1981). Based on a simple AR(1) model of the asset price and the empirical frequency distribution of prices, Norman derives a trading rule that generates a buy signal whenever the vessel value falls below a certain threshold and a sell signal when the value rises above the same threshold. Norman reports a return on capital of 15.6% for the optimal threshold, corresponding to being in the market 84% of the time. However, he does not report the return on capital from a benchmark buy-and-hold strategy. Marcus et al (1991) develops an investment strategy based on the deviation in vessel value from the fundamental value (nominal production cost). Although their approach is based on the observed cyclical nature of the bulk shipping markets, the authors introduce exogenous variables, and, accordingly, their work can not be considered as strictly technical analysis.

3 Data snooping

An important issue generally encountered, but rarely directly addressed when evaluating technical trading rules, is data snooping. Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection. The potential impact of data snooping on the performance of technical trading rules was recognized early on by Jensen and Bennington (1970) who refer to it as a "selection bias". Data snooping can be a result of a particular researcher's efforts, or it can result from a subtle survivorship bias operating on the entire universe of technical trading rules. Rules that happen to perform well historically receive more attention, and if enough parameterizations are considered over time, some rules are bound by pure luck to produce superior performance even if they do not genuinely have predictive power. Negative results are ignored, while positive results are published and taken to indicate that trading rules can yield profits. For example, there is a vast literature on pricing anomalies in the equity markets, summarized by Ball (1995) and Fortune (1991). Roll (1994) finds that these aberrations are difficult to exploit in practice, and suggests that they may be partially the result of data mining. Lo and MacKinlay (1990) try to quantify the effects of data snooping in financial asset pricing models. Although technical analysis has not been used extensively by researchers or investors in the bulk shipping markets, the adoption of well-known trading rules from the stock and foreign exchange markets may introduce exactly the same selection bias in this case. In addition, the selection of the "best" trading rule from a large universe of rules and parameterizations is a data mining exercise in itself.

Previous research (e.g. BLL 1992) has evaluated the statistical significance of the findings by fitting several models to the raw data and re-sampling the residuals to create numerous bootstrap samples. The bootstrap approach introduced by Efron (1979) is not new to the evaluation of technical analysis. The idea is to check if the technical trading rules are robust to other specification of the return generating process by calculating p-values from a simulated empirical distribution. Isakov and Hollistein (1998) acknowledge that the predictability of asset returns could be due to some well-known features of the data such as non-normality, serial correlation and time-varying moments, and perform bootstrap tests to check if these features bias the test statistics. Assuming that the returns follow an AR(1) and a GARCH(1,1) process, their results indicate that, although the features are present in the data, they are not the cause of profitability (in the absence of trading costs) of the technical trading rules.

As acknowledged by BLL (1992), such bootstrap tests are not able to compute a comprehensive test across all rules, as such a test would have to account for dependencies between results for different trading rules. They try to mitigate this problem: (1) by reporting results from all their trading strategies, (2) by using a very long data series, and (3) emphasizing the robustness of results across non-overlapping sub-periods for statistical inference. As an alternative, Lo and MacKinlay (1990) recommend a ten-year out-of-sample performance experiment as a way of purging the effects of data-snooping biases from the analysis. Similarly, as a solution to the data-mining problem, Neely, Weller and Dittmar (1997) apply genetic programming techniques to the foreign exchange market. Genetic programming is a method by which a computer searches through the space of technical trading rules to find a group of rules that generate positive excess returns. These good rules are then tested on out-of-sample data to see if they continue to generate positive returns. STW (1998) adopt a modified "Reality Check Bootstrap" introduced by White (1997) that provides a procedure to test whether a given model has predictive superiority over a benchmark model after accounting for the effects of data-snooping. The approach of STW is adopted in this paper and described in section 4.

4 Data description

There is an evident lack of standardization in the shipping industry. Almost every vessel is unique, with its own cargo size, cargo type, speed, age, quality and fuel consumption. All these factors affect the price a vessel would obtain in the second-hand market. Moreover, the second hand markets for ships generally have a low turnover. In the large tanker category (200,000DWT+[1]), a total of 187 vessels were reported sold in the second-hand market from January 1990 to March 1999[2] corresponding to an average annual turnover of 5% of the fleet. For smaller vessel sizes the world fleet is larger, and, accordingly, the liquidity is better. The lack of standardization and a liquid asset market entail the use of shipbrokers' estimates for a standardized vessel in place of actual transaction data. Such historical valuation estimates are typically published on a monthly basis and consist of vessel values for, say, a five-year-old vessel. That is, the depreciation in asset value due to aging needs to be taken into account. Brokers who value ships generally take the same view as accountants, writing down the vessel value to scrap value linearly over 15 or 20 years. The same "rule of thumb" is used in this paper due to the lack of a better estimate.

The freight markets in the various bulk shipping sectors are very liquid compared to the S & P markets, with several fixtures of vessels taking place every day, on average. However, the short-term (daily) freight rate variations resulting from the clearing of cargoes and vessels available in a certain loading area are not necessarily indicative of the longer-term swings in the freight rate. As the technical trading rules in this context concern the investment/divestment of a physical asset with holding periods of months or years, the use of less frequent observations (weekly or monthly averages) is more appropriate. Moreover, a roundtrip for an oceangoing vessel will typically take a month or more, and, thus, any short-term freight rate variations has little impact on the voyage profit of a certain vessel. Also, in practice, other factors such as the

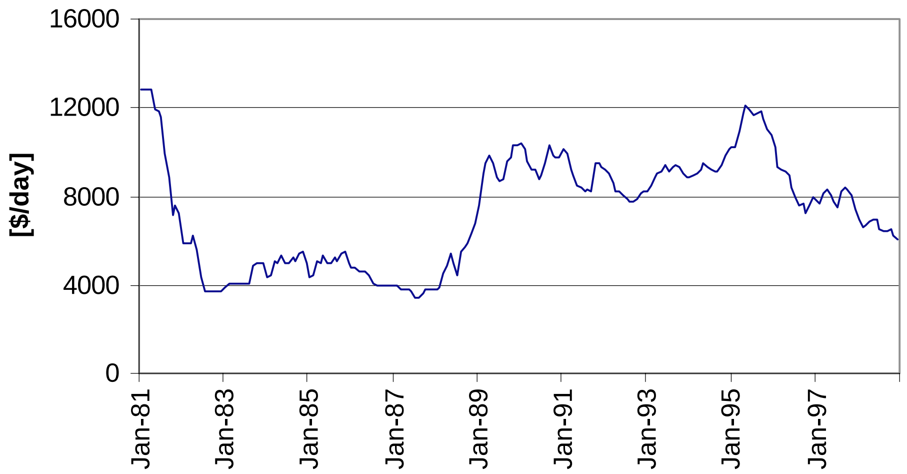
[1] DWT - deadweight [tons] measures the cargo capacity of a ship.

[2] Source: MaritimeData.com

relatively large trading cost[3] and the required time to complete a transaction prohibit trading on short-term signals.

The data in this paper concern a small Products Carrier, which is a tanker that typically transports clean oil products such as gasoline from the Caribbean to the U.S. and in Asian trades. Monthly shipbroker estimates of freight rates and vessel values between January 1981 and December 1998 are illustrated below. The data set consists of only n = 216 observations, which admittedly is a small sample size in this context. However, given the practical concerns above, it will have to do as a first cut.

Figure 1: Timecharter freight rates, products carrier 38,000 DWT



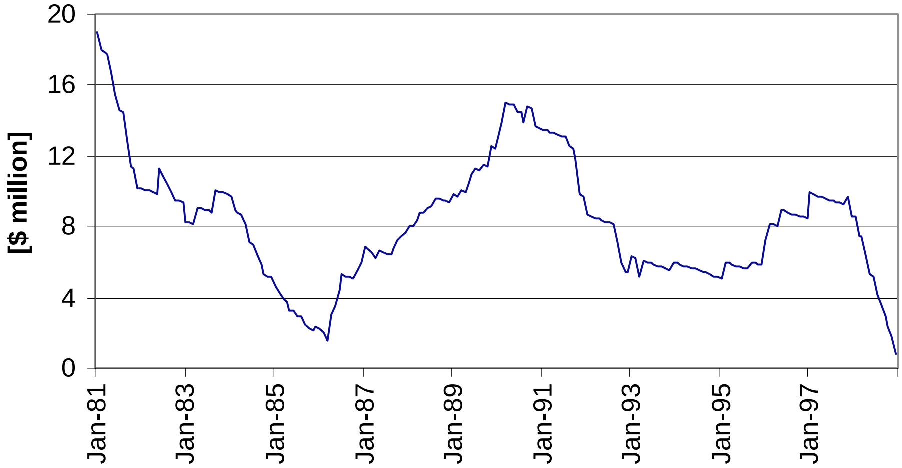
Source: Fearnleys AS, Oslo, Norway

The daily operating profit is calculated by subtracting the daily operating costs from the timecharter freight rate. Although the operating cost will escalate due to inflation and physical wear and tear, it has been fixed at $4,000/day in this paper due to the lack of a satisfactory time series. Furthermore, the effect of lay-up as a measure to limit losses at low freight rates is ignored. For the buy-and-hold strategy, it is assumed that the vessel is bought five years old in the beginning of 1981 for $19 million and that its book value is linearly depreciated to scrap value (approx. $1

[3] The trading cost consists of a commission to the shipbroker, typically 1% of the vessel value and paid by the seller, as well as any costs of transferring the ownership.

million) over the last 18 years, corresponding to $1 million annually. The resulting price development for a 1976-built product carrier is illustrated in the figure below.

Figure 2: Vessel value 1976-built product carrier



Source: derived from Fearnleys AS, Oslo, Norway

Note that the vessel would have been scrapped at the end of 1998 when the value as a going concern falls below the scrap value. In the subsequent sections, the trading signals are generated on the basis of vessel values alone, although it can be argued that the technical trading rules should be assessed on the basis of a price series that incorporates the information inherent in the freight rate series. However, operating profits ("dividends") is included when calculating the returns from the technical trading rules. The monthly returns for the buy-and-hold strategy are illustrated below.

Figure 3: Period returns (monthly)

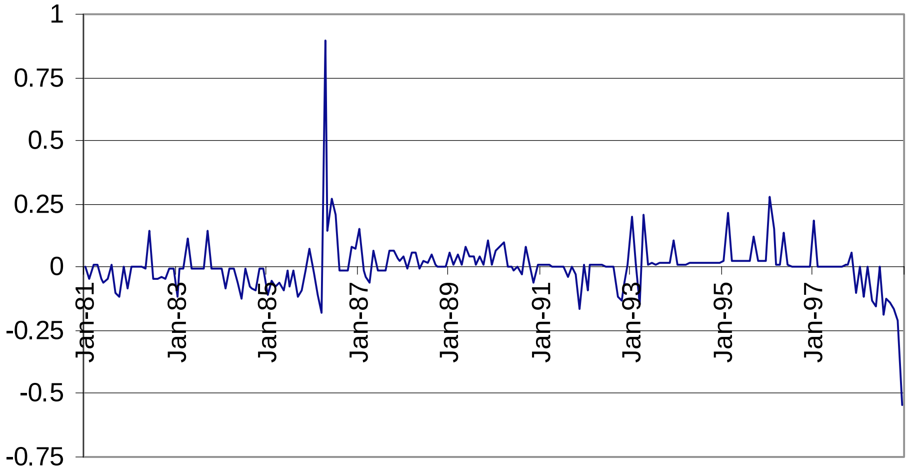


Table 1 : Summary statistics for monthly returns of the buy-and-hold strategy

Mean	0.003244
Standard Error	0.007006
Standard Deviation	0.102963
Kurtosis	29.90262
Skewness	2.535463
Minimum	-0.54724
Maximum	0.900613
ρ(1)	0.225*
ρ(2)	0.213*
ρ(3)	0.185*
ρ(4)	0.163*
ρ(5)	0.154*

*Significant at the 5% level for a two tailed test

The average monthly return for the buy-and-hold strategy corresponds to 4.0% annually, which is less than the risk-free interest rate during the time period. This is a typical phenomenon in the shipping industry as investors seem to be attracted by the potential for large short-term profits rather than a decent long-term return. The figures in table 1 show that the return series is asymmetric as indicated by the positive skewness coefficient and that it is leptokurtic, i.e. it has fatter tails than the normal distribution. There is also a significant positive short-term autocorrelation in the monthly returns up to the fifth order.

5 Methodology

5.1 The universe of trading rules

As technical analysis is not widely used in the shipping industry, it is necessary to specify an appropriate universe of trading rules based on previous academic studies of financial markets and the technical analysis literature. The magnitude of data-snooping effects on the assessment of the performance of the best trading rule is determined by the dependence between all the trading rules' payoffs, so the design of the universe is important. However, as the application of technical analysis to this market is a new approach, the parameterizations (ref. appendix A) of the large number (1053) of technical trading rules are chosen more or less arbitrarily. The focus in this paper is on filter rules, support and resistance levels, and moving averages, the principles of which are described below.

5.1.1 Filter rules

Fama and Blume (1966) explain the standard filter rule as follows:

"An x per cent filter is defined as follows: If the daily closing price of a particular security moves up at least x per cent, buy and hold the security until its price moves down at least x per cent from a subsequent high, at which time simultaneously sell and go short. The short position is maintained until the daily closing price rises at least x per cent above a subsequent low at which one covers and buys. Moves less than x per cent in either direction are ignored."

A subsequent high is interpreted as the highest closing price achieved while holding a particular long position. Likewise, a subsequent low is the lowest closing price achieved while being out of the market (no short sales are possible).

5.1.2 Moving averages

The standard moving average (MA) cross-over rule generates a buy (sell) signal when the asset price penetrates the MA from below (above). Hence, a long position is retained as long as the price trend remains above the MA, alternatively, as long as a fast MA remains above a slow MA, where the slow MA is calculated over a greater number of months. Two types of filters may be imposed to filter out false (loss-making) trading signals. The fixed percentage band filter requires that the difference between the slow MA and the fast MA exceeds b% of the slow MA in order to execute a buy or sell signal. The introduction of a band reduces the number of "whiplash" buy and sell signals when the short and long-term moving averages are close. The time delay filter requires that the signal remain valid for a certain number of months, c, before action is taken.

5.1.3 Support and resistance levels

A simple trading rule based on the notion of support and resistance levels is to buy when the closing price exceeds the maximum price over the previous n months, and sell when the closing price is less than the minimum price over the previous n months. As with the moving average rules, a fixed percentage band filter, b, and a time delay filter, c, is included.

5.2 Performance measure

The test procedure is based on the l x 1 performance statistic:

$$\bar{f} = n^{-1}\sum_{t=R}^{T} \hat{f}_{t+1}$$

Where l is the number of technical trading rules, n is the number of prediction periods indexed from R through T so that T = R + n - 1, and $f_{t+1} = f(\beta_t)$ is the observed performance measure for period t + 1. In this application n = 198 and R = 18, accommodating technical trading rules that need 18 months of data in order to produce a trading signal. The various parameterizations of the trading rules (β_k,k = 1,…,l) generates the returns that are used to calculate the performance measure. The form for $f_{k,\, t+1}$ is adjusted slightly compared to previous literature (e.g. STW 1998) to account for the period vessel operating profits (Z_t) during a long position:

$$f_{k,t+1} = \ln[1 + y_{t+1}S_k(\chi_t, \beta_k)] - \ln[1 + y_{t+1}S_0(\chi_t, \beta_0)], k = 1,.....,l$$

Where

$$\chi_t = \{X_{t-i}\}_{i=0}^{R}$$

X_t is the price series of vessel values, $y_{t+1} = (X_{t+1} + Z_t - X_t)/X_t$, and $S_k(\cdot)$ and $S_0(\cdot)$ are signal functions that convert the sequence of price index information χ_t into market positions. $S_k = 1$ represents a long position and $S_k = 0$ represents a neutral position (out of the market). In other words, we assume that short selling has not been possible in this market during the time period under investigation. This is consistent with the opinions of industry practitioners. The lack of a maritime derivatives market would have prevented a synthetic replication of short sales. However, another way to achieve similar results is to use the following strategy: when an investor observes a buy signal he borrows half of the vessel value. This yields twice the market return less the borrowing rate. When the investor observes a sell signal, he sells the vessel and invests all his money in a risk-free asset. If the frequency and duration of long and neutral (sell) positions is similar and the borrowing rate is close to the lending rate such a strategy would yield similar results to a long-short strategy. This is also a strategy that is used by most shipowners, as very few use only owners' equity for vessel purchases. However, this approach is not implemented here, which means the calculated mean returns from the use of the trading rules are conservative.

The natural null hypothesis is that the performance of the best technical trading rule is no better than the performance of the benchmark position. Thus, if f_k is the excess return over the benchmark strategy corresponding to trading rule k:

$$H_0 : \max_{k=1,\dots,l} \{E(f_k)\} \leq 0$$

Rejection of this null hypothesis indicates that the best trading rule achieves performance superior to the benchmark. Following the discussion above, a suitable interpretation in this market is to regard the benchmark as the return from a buy-and-hold strategy where $S_0 = 1 \ \forall \ t$. It is assumed throughout the study that an investor in a neutral position obtains a risk-free interest rate equal to *zero* on his wealth.

In order to replicate real-life trading conditions, a transaction cost of 1% of the vessel value is subtracted at the time of a sale. Moreover, in a low-volume market such as the second-hand sale & purchase market for ships one may experience problems similar to non-synchronous trading effects in the financial markets, as a shipowner is not likely to be able to purchase or sell a vessel on short notice. There simply may not be a suitable vessel for sale at the time of a "buy" signal, or an interested buyer at the time of a "sell" signal. Alternatively, the pre-purchase activities such as the inspection of a potential vessel and the price negotiation may take several weeks. To address this issue, a trading signal observed in month t can be implemented in month t+1. This issue is not explicitly treated here. However, the empirical results indicate that the introduction of a time delay in the execution of a buy or sell signal generally has a negative effect on the returns of a technical trading rule.

White (1997) shows that H_0 can be evaluated using the stationary bootstrap of Politis and Romano (1994) to the observed value of $f_{k,t}$. Following the notation of STW (1998), resampling the returns from the trading rules yields B bootstrapped values of f_k, denoted as $f^*_{k,j}$, where i indexes the B bootstrap samples. Consider the statistics

$$\bar{V}_l = \max_{k=1,\dots,l}\left\{\sqrt{n}\left(\bar{f}_k\right)\right\},$$

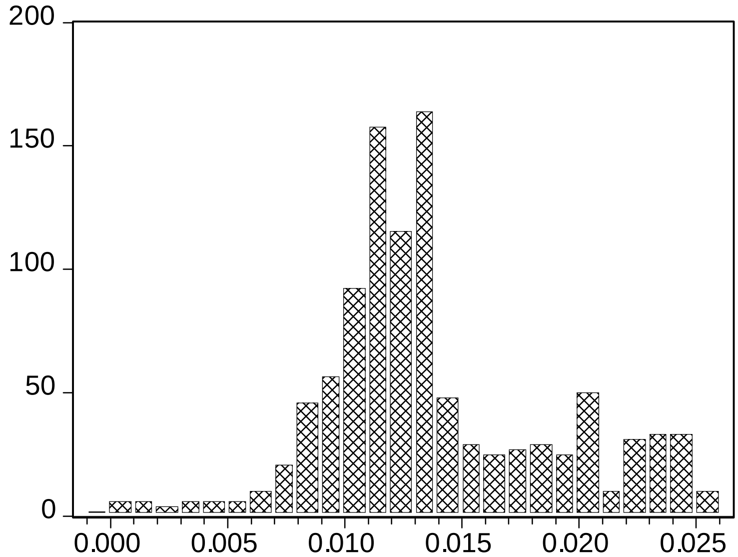
$$\bar{V}^*_{l,j} = \max_{k=1,\dots,l}\left\{\sqrt{n}\left(\bar{f}^*_{k,i} - \bar{f}_k\right)\right\}, i = 1,\dots,B$$

By comparing V_l to the quantiles of $V_{l,i}$ one obtains White's Reality Check p value for the null hypothesis. By employing the maximum value over all the *l* trading rules, the p value incorporates the effects of data-snooping from the search over the l rules.

6 Empirical results

Unfortunately, the data set is not large enough to permit a meaningful out-of-sample experiment or a meaningful investigation of the robustness of results across non-overlapping sub-periods. This complicates a statistically precise evaluation of the trading rule performance. At first sight, the performance of the technical trading rules seems very convincing. Out of all the 1053 parameterizations, only ONE trading rule results in a negative mean return f_k compared to the benchmark buy-and-hold strategy. Moreover, none of the trading rules results in a negative net cumulative wealth, even when accounting for trading costs. The net cumulative wealth is calculated as the sum of all trading profits/losses, both from vessel operation and asset play. The figure below presents the histogram of mean returns:

Figure 4: Overall trading rule performance (monthly mean returns)



Series: RETURNS
Sample 1 1053
Observations 1053

Mean	0.013867
Median	0.012907
Maximum	0.025233
Minimum	-0.000736
Std. Dev.	0.004926
Skewness	0.446040
Kurtosis	3.116844
Jarque-Bera	35.51501
Probability	0.000000

Due to the apparent superior performance of many of the 1053 trading rules considered, the consideration of dependencies between trading rules (data snooping effects) is unlikely to overturn a conclusion that the best-performing trading rule outperforms the buy-and-hold strategy. In the 18-year period from 1981 to 1998 the best-performing trading rule according to the mean return criterion is a filter rule with an average annualized excess return compared to the return from the buy-and-hold strategy of 34.9%. The corresponding net profit over the full time period is $23.84 million, or $23.35 million after trading costs.

Note that the best-performing trading rule according to the mean return criterion is not necessarily the parameterization that results in the highest cumulative net wealth. When the investor is long the excess return is zero, as the benchmark is the buy-and-hold strategy. Consequently, this criterion favors trading rules that are better at predicting downturns in the market (when the excess return in positive) and not up-turns which is when the investor will actually make money given that short sales are not possible. Due to the small number of trades, the trading costs have little impact in this market.

The table below reports the statistics for the best-performing trading rule according to the mean return criterion. Note that the mean returns for the long and neutral positions in table 2 are absolute returns rather than excess returns compared to the buy-and-hold strategy.

Table 2: Best-performing trading rule according to mean return criterion

Description	N(long)	N(neutral)	#trades	μ(long) [σ]	μ(neutral) [σ]
Filter rule x = y = 0.03	121	77	7	0.028993 [0.06171]	-0.03175 [0.144272]

N(long) and N(neutral) is the number of months an investor is long or neutral respectively. μ(long) and μ(neutral) reports the mean monthly return obtained in long or neutral positions, with the sample standard deviation in brackets.

According to the best trading rule, the investor would have been in the market 61% of the time and made seven trades (buy + sell). The table indicates that the trading rule is capable of identifying market trends, as the mean return in long positions is positive (40.9% p.a.) while the mean return in neutral positions is negative (-45.5% p.a.). In terms of volatility, returns associated with long positions have a lower standard deviation than returns associated with neutral (sell) positions. This is consistent with a well-known feature of asset returns called the leverage effect and initially documented by Black (1976). Moreover, an investor who used the best trading rule for asset play would have obtained returns (in long positions) that are higher than the returns of the buy-and-hold strategy and yet have lower standard deviation (ref. table 1). From a risk-reward point of view, this observation supports the notion that the best technical trading rule outperforms the benchmark buy-and-hold strategy.

Assume for a moment that the distribution of returns in this market is normal, stationary and time-independent so that the standard t-ratio tests are applicable. The corresponding t-statistic to test the null hypothesis that the buy/sell mean return according to the best trading rule is equal to the buy-and-hold strategy is given by (BLL 1992):

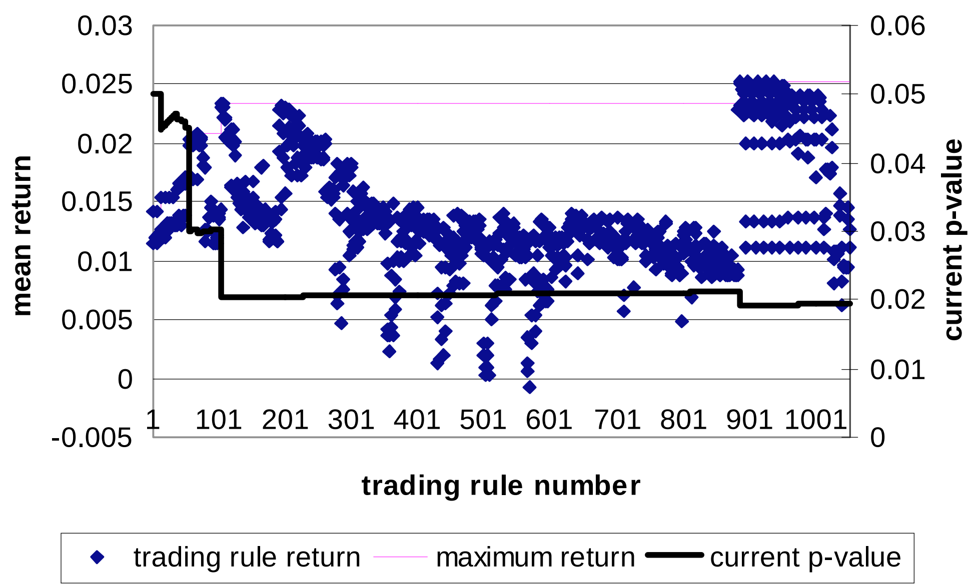
$$t = \frac{\mu_r - \mu}{\left(\frac{\sigma^2}{n} + \frac{\sigma^2}{n_r}\right)}$$

where μ_r and n_r are the mean return and total duration of the long/neutral positions, and μ and n are the unconditional return from the buy-and-hold strategy and the total number of observations. σ^2 is the estimated variance for the entire sample. The resulting t-statistics are 2.17 and -2.53 for the long and neutral positions respectively. Hence, the mean returns obtained by using the trading rule are significantly different from the return of the buy-and-hold strategy at standard levels of significance. Of course, the returns do not satisfy the assumptions behind these calculations. Nevertheless, these results support the notion that the best-performing technical trading rule outperforms the benchmark.

The results so far are intriguing but it remains to be seen whether the results stand up to an adjustment for data-snooping/data-mining effects. After all, the best trading rule is drawn from a large universe of parameterizations. Following STW (1998), two possible outcomes can occur when an additional trading rule is inspected. If the marginal trading rule does not lead to improvement over the previously best-performing trading rule, the p-value for the null hypothesis that the best model does not outperform will increase, effectively accounting for the fact that the best trading rule has been selected from a larger set of rules. On the other hand, if the marginal trading rule improves on the maximum performance statistics, then this can reduce the p-value since better performance increases the probability that the optimal model genuinely contains valuable economic information. The principle is similar to the reasoning behind the Akaike and Schwarz information criteria, which penalize the R^2 value if the introduction of an additional variable in a regression fails to improve the R^2 value sufficiently.

The figure below provides an illustration of these effects operating sequentially across the full universe of trading rules. The figure illustrates the development in maximum mean return performance and p-value for the null-hypothesis as more trading rules are considered. The data-snooping adjusted p-value is calculated according to White's Reality Check as explained in section 5 with B = 500 bootstrap samples.

Figure 5: Economic and statistical performance of the best rule



The figure plots each trading rule against its mean return (measured on the left y-axis). The upper line tracks the highest mean return up to an including a given number of trading rules (indicated on the x-axis). The lower line indicates the bootstrapped p-value (right y-axis). The maximum mean return starts out around 0.014 (16% p.a.) and quickly increases to 0.023 (32% p.a.), yielding a p-value of 0.02 after the first 120 trading rules have been considered. After approximately 900 trading rules have been considered, the best performance is improved to the final 0.025 (35% p.a.) and the p-value is kept to a level of less than 0.02. Ultimately, the only numbers that matter are those at the extreme right of the graph, as the order of experiments is arbitrary. Note that what appears to be vertical clusters of mean return points simply reflect the performance of neighbor trading rules in a similar class as the parameters of the trading rules are varied.

7 Conclusions and discussion

All the findings in this paper support a conclusion that the best-performing technical trading rule is capable of outperforming the benchmark and that the model has superior predictive power. Of course, there is no guarantee that this apparent superior performance will continue in the future, and the ultimate test of the best-performing trading rule would be an out-of-sample test after another ten years of data. A further issue at stake is how an investor could have possibly determined the best trading rule prior to committing money to a given rule. Admittedly, there is no indication that it would be possible to find ex ante the trading rule that will perform the best in the future, and the probability that an investor would pick a trading rule with an excess mean return that is statistically significant is rather small.

Consequently, whether the results in this paper have implications for weak form market efficiency is a very subjective topic. In general, two competing explanations for the presence of predictable variations in asset returns have been suggested: (1) market efficiency in which prices take swings from their fundamental values, and (2) markets are efficient and the predictable variation can be explained by time-varying equilibrium returns. There is little evidence so far that unambiguously distinguishes these two competing hypotheses. STW(1998) argues that the existence of outperforming trading rules would only seem to have implications for weak form market efficiency or variations in ex ante risk premia if the rules under consideration are known during the sample period. The application of technical trading rules to maritime financial data series has hardly received any attention from researchers, and it is questionable whether the market players in the industry are sophisticated enough to utilize such investing tools. On the other hand, the types of trading rules considered would have been well known from other financial applications throughout the time period.

Given that investors have had the opportunity to utilize such trading rules, there may be market-specific reasons why predictable and abnormal returns seem to exist in this market and why these abnormalities haven't been "traded away". Firstly, a potential reason may be barriers of entry in terms of knowledge. However, an investor can outsource every aspect of the daily operation of the ship, turning the deal into a pure value play. Secondly, perhaps there is an attitude in the global financial community that shipping is a niche industry for people who take a special interest, and that what is considered minor investment opportunities aren't worth pursuing. The main problem is most likely the small size of the market in terms of number of vessels in any given category, and the resulting low liquidity. In other words, there may not be a vessel for sale when the technical trading rule generates a buy signal or a buyer when the trading rule generates a sell signal. Such practical issues may make implementation difficult and reduce the effective returns generated by any trading rule. Although trading costs have been treated in this paper, the effects of an illiquid market have not been fully considered. The introduction of a time delay in some of the trading rule parameterizations indicates that a delay in the execution of a buy or sell signal has a negative effect on returns. A thorough treatment of this issue in a future edition may overturn the conclusion in this paper.

Appendix: Trading rule parameters

This appendix describes the 1053 parameterizations used to generate the universe of trading rules.

A.1 Filter rules

x = change in security price (X $\times$ price) required to initiate a position

y = change in security price required to liquidate a position

x, y = 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.15. 0.20, 0.25

Allowing all combinations of x and y there are x $\times$ y = 169 filter rules

A.2 Moving average rules

n = number of months in a slow moving average = 2,…., 18

m = number of months in a fast moving average = 1,…., 6

b = fixed band multiplicative value = 0.01, 0.02, 0.03, 0.04, 0.05

c = number of months for the time delay filter = 2, 3, 4

Noting that m must be less than n, there are 87 combinations of m and n.

Total number of MA rules:

87 + b $\times$ 87 + c $\times$ 87 = 783

A.3 Support and resistance rules

n = number of months in the support and resistance range = 6,…,18

b = fixed band multiplicative value = 0.01, 0.02, 0.03, 0.04, 0.05

c = number of months for the time delay filter = 2, 3

Total number of S & R rules:

13 + 13 $\times$ b + 13 $\times$ c = 104

Bibliography

Alexander, S. (1961): "Price movements in speculative markets: Trends or random walks", Industrial Management Review 2, 7 - 26.

Alexander, S. (1964): "Price movements in speculative markets: Trends or random walks, no 2", in P. Cootner, ed.: The Random Character of Stock Market Prices, MIT Press, Cambridge, Mass.

Ball, Ray (1995): "the theory of Stock market efficiency: Accomplishments and Limitations", Journal of Applied Corporate Finance, 4 - 17.

Black, F. (1976): "Studies of stock prive volatility changes", Proceedings of the American Statistical Association, 177 - 181.

Brock, William, Josef Lakonishok, and Blake LeBaron (1992): "Simple technical trading rules and the stochastic properties of stock returns", Journal of Finance 47, 1731-1764.

Cutler, David, James M. Poterba and Lawrence Summers (1990): "Speculative Dynamics and the Role of Feedback traders", AEA Proceedings and papers, Vol. 80, No. 2, 63 - 68.

Efron, Bradley (1979): "Bootstrap methods: Another look at the jackknife", Annals of Statistics 7, 1 - 26.

Fama E. F. and Blume, Marshall (1966): "Filter rules and stock market trading profits", Journal of Business 39, 226 - 241.

Fortune, Peter (1991): "Stock market efficiency: an autopsy?", New England Economic Review, Federal Reserve Bank of Boston, 18-40.

Gartley, H.M. (1935): "Profits in the stock market", Lambert-Gann Publishing Company, Pomeroy, Washington.

Hudson, R., Dempsey M, and K. Keasey (1996): "A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994, Journal of Banking and Finance 20, 1121 - 1132.

Isakov, D. and Hollistein, M (1998): "Application of simple technical trading rules to Swiss stock prices, Is it profitable?", Research paper No 2, FAME, Geneva Switzerland.

Jensen, Michael and George A. Bennington (1970): "Random walks and technical theories, Some additional evidence", Journal of Finance 25, 469-482.

Kho, B. C. (1996): "Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets", Journal of Financial Economics 41, 249-290.

Levich, Richard and Lee, Thomas (1993): "The significance of technical trading rule profits in the foreign exchange market: a bootstrap approach", Journal of International Money and Finance 12, 451-474.

Lo, Andrew W. and Craig MacKinlay (1990): "Data-snooping biases in tests of financial asset pricing models", The Review of Financial Studies 3, 431-467.

Marcus, H.S., Glucksman, M, Ziogas, B, and Meyer, Karl (1991): "A buy-low, sell-high investment methodology: The case of Bulk Shipping", Interfaces 21, 8 - 21.

Norman, Victor (1981): "Market strategies in bulk shipping", working paper, Norwegian School of Economics and Business Administration, Bergen, Norway.

Neely, C., Paul Weller, and Robert Ditmar (1997): "Is technical analysis profitable in the foreign exchange market? A genetic programming approach", Journal of Financial and Quantitative Analysis.

Osler, Carol and Kevin Chang (1995): "Head and shoulders: Not just a flaky pattern", Federal Reserve Bank of New York Staff Report 4, 1 - 65.

Politis, Dimitris and Joseph Romano (1994): "The stationary bootstrap", Journal of the American Statistical Association 89, 1303 - 1313.

Roll, Richard (1994): "What every CFO should know about scientific progress in financial economics: what is known and what remains to be resolved", Financial Management, 69-75.

Stopford, Martin (1997): "Maritime Economics", Second edition, Routledge, London.

Sullivan, Ryan, Allan Timmermann, and Halbert White (1998): "Data-snooping, Technical Trading Rule Performance, and the Boostrap", working paper UCSD, forthcoming Journal of Finance, October 1999.

Sweeney, Richard (1988): "Some new filter rule tests: Methods and results", Journal of Financial and Quantitative Analysis 23, 285-300.

White, Halbert (1997): "A reality check for data snooping", technical report, NRDA, San Diego, CA.