

MODELLING AND TRADING: PORTFOLIO USING TECHNICAL TRADING RULES

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ABSTRACT

This research examines and analyses the benefits of technical trading rules in multiple asset portfolios for forecasting and trading models previously done by Dunis and Miao (2004) that has been investigated for technical analysis, validating its benefits. In this research, we are particularly interested in evaluating the performance and efficiency of some of these technical trading rules in well diversified portfolio. The study finds that technical rules help determine the advantages of diversifying weighted assets portfolios.

The research looks at the performance of technical trading rules applications using automated models by optimising the trading rules on the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures for last six years, while benchmarking the portfolio's results with a previous study by Dunis and Miao (2004).

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1. Introduction

The motivation to outperform simple buy-and-hold strategies has always brought new tools and trading strategies to global financial market. Numerous techniques to gain abnormal profits have been extensively published to forecast financial markets by academia and practitioners, they fall into two main categories: fundamental analysis and technical trading rules.

In this study we will focus on technical trading rules. There are various technical rules that are commonly accepted by market practitioners, which have been proven to outperform simple buy-and-hold strategies from time to time. In addition, with the trading rules using daily or more frequent data, different profitable trading strategies can be implemented with the selection of the right rules.

There is a belief in the ability to of technical rules to generate abnormal profits. This contradicts, that the efficient market hypothesis, which says that markets fully integrate all of the available information and therefore prices are fully adjusted, once new information becomes available. If this is the case, we can say that efficient markets make prediction useless. In reality market reaction to new information is not necessarily immediate. Therefore, we can say that historical analysis is useful in diagnosing repeated pattern behaviors leading to active investment strategies that generate better-than-market returns. We usually refer them as technical trading rules.

Technical trading rules have been seen as important investment tools of increasing returns. This research examines and analysed the benefits of technical trading rules in the context of a multiple asset portfolio of trading models. Numerous studies have been performed to determine whether such rules can be employed to provide superior investing performance. In this research, we are particularly interested in evaluating the performance and efficiency of some of these technical trading rules while diversifying in an equally weighted portfolio. The study finds technical rules help determine the distribution of assets in the portfolio. The widely used technical trading rules are used for forecasting and trading are detailed in Chapter 5.

The trading models are estimated in terms of forecasting accuracy and in terms of trading performance via a simulated trading strategy based on market data. In evaluating the benefits of various technical trading models using financial criteria, such as risk-adjusted measures of return, annualized return, Sharpe ratio and maximum drawdown, also assessed using forecasting accuracy measures, such as root mean squared (RMS) errors.

The motivation for this research is to determine the added value associated with several trading models on an asset portfolio by benchmarking results to previous work done by Dunis and Miao (2004). Their study covers the performance of MACDs with no Filters, with Vol. Filter #1 (No-Trade), and Vol. Filter #2 (Reverse). The technical trading models are developed for the EUR/USD Exchange rates², LME-Copper

²The EUR/USD exchange rate only exists from 04/01/1999, we follow the approach of Dunis and Williams (2002) to apply a synthetic EUR/USD series from 02/01/1995 to 31/12/1998 combining the spot USD/DEM and the fixed EUR/DEM exchange rate.

futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures³, CME-S&P 500 Index futures for last six years⁴. Using daily data from 2nd January 1998 to 31st December 2002 for in-sample estimation, leaving the period from 2nd January 2003 to 31st May 2004 for out-of-sample forecasting. Using Moving Average, Double Moving Average, Range Break, Filter Rule, ARMA and ARMA-Garch model.

2. Literature Review

Market Efficiency

One of the main subjects of financial market since the 1960's has been the concept of the efficient capital market. In the framework of capital markets, the term efficient market has a very specific meaning, one in which the prices of securities fully reflect all available information (Elton and Gruber (2003)).

The definition "Efficient Markets Hypothesis" (EMH) would be an extremely hard hypothesis to meet under conditions found in the real world, because the information is at least not free. It is perhaps more realistic to include the following condition: prices reflect information until the marginal costs of obtaining the information and trading no longer exceed the marginal benefit (Elton & Gruber (1995)) and prices should reflect information as soon as possible.

Technical Trading rules

Technical Trading rules began to emerge a century ago but the use of latest technological advancement has made these analyses more practical. Bachelier (1900), wrote the seminal paper *Théorie de la spéculation* in 1900, in this paper a number of statistical models are developed including what would later be known as Brownian Motion. Andreou, Pitts and Spanos (2001) trace the development of this work, in an attempt to discover how these models capture the empirical irregularities inherent in economic data.

Studies such as Pruitt and White (1988) and Dunis (1989) directly support the use of technical trading rules as a means of trading financial markets. Trading rules such as moving averages, filters and patterns seemed to generate returns above the conventional buy and hold strategy. Lukac and Brorsen (1990) carried out a comprehensive test of futures market trading. They found that all but one of the trading rules tested generated significantly abnormal returns.

Brock, W., Lakonishok, J. and LeBaron, B. (1992) studied the forecasting accuracy and trading performance of several traditional techniques. The study was based on the data series of Dow Jones Industrial Average from first trading days in 1897 to last trading day in 1985. Two Trading methods were used in there study: moving average and trading range break. The returns conditions were based on signal on buy or (sell) from the actual DJIA data are compared to returns from simulated comparison series generated by the fitted model. They conclude that statistical forecasting accuracy that 26 of these trading rules outperformed a benchmark of holding cash.

³ The series is converted into USD, using the same set of series EUR/USD

⁴ The financial datasets used in this study are daily data obtained from DataStream.

In addition, Kwon and Kish (2002) indicate that technical trading rules add value over a buy-and-hold strategy. This study consists of an empirical analysis on technical trading rules (the simple price moving average, the momentum, and trading volume) utilizing the NYSE value-weighted index over the period 1962 to 1996, as well as three sub periods. The methodologies employed include the traditional t-test and residual bootstrap methodology utilizing random walk, GARCH-M with some instrument variables. The results indicate that the technical trading rules add value to capture profit opportunities over a buy-hold strategy. When the trading rules are applied to the different sub-samples. The results are weaker in the last sub-period, 1985 to 1996 this may imply that the market is getting efficient in information over more recent years because of technological improvements.

On the other hand, the issue of transaction cost in technical trading rules has been examined by Hudson et al. (1996) using British data. Their results find no significant difference from buy and hold strategies when transactions cost data are included. However, Isakov and Hollistein (1998) report that transaction costs eliminate technical trading profits in the Swiss market, however they suggest conditions where large investors may profit from moving average trading rules

Yochanan, Uri, Paul and Joseph (2001) examine the efficiency of using four moving average models in the emerging market of Israel through the analysis of the Tel-Aviv 25 Index (TA25), and compare it to the performance of the S&P 500. They concluded that the moving average method could beat that simple buy – and – hold strategy on the TA25.

Portfolio Diversification

Notable contributions in the area of diversification include Markowitz (1952) Tobin (1958) and Grubel (1968) they all shows that the correlations of returns among different stock markets are low thus benefiting portfolio diversification. Further discussion is presented in chapter 6.

Markowitz (1952) discusses how risk adverse investors can be construct portfolios in order to optimize expected returns for a given level of market risk. The theory quantifies the benefits of diversification. Using number of risky assets, an efficient frontier of optimal portfolios can be constructed. Each portfolio on the efficient frontier offers the maximum possible expected return for a given level of risk.

Several studies namely by Pruitt and White (1988), Taylor and Allen (1992) and Menkhoff (1997) point to evidence that suggests that technical analysis is used extensively by foreign exchange professionals at all levels.

According to Acar and Lequeux (1995), fundamentally and empirically, there is little return enhancement when adopting a passive approach to the currency markets. Levich and Thomas (1993b), using a currency overlay, hedge a position dynamically in the bond market and show that this is profitable. Acar and Lequeux (1996) also construct a currency overlay for major currency pairs and find that even if markets follow a random walk, dynamic overlays still have the potential of reducing the risk of international portfolios.

A study by Strange (1998) indicates that currency based overlay managers have added considerable value, consistently over the past ten years and in addition have reduced risk as measured in the standard deviation versus the benchmark value. This is backed by Baldrige, Meath and Myers (2000).

3. Data & Methodology: The Financial Data Time Series

The implication for forecasting applications is that in most conditions considering data and time lags, in any time series analysis it is critical that the data used is clean and error free since the learning process of the patterns is totally data-dependent Dunis and Williams (2002). It is significant in the study of financial time series forecasting considering, which type of data from the market sampled is required. The sampling frequency depends on the objectives of the researcher and the availability of data. For example, intraday time series can be extremely noisy and “a typical off-floor trader would most likely use daily data if designing a neural network as a component of an overall trading system” (Kaastra and Boyd, 1996: 220).

The financial datasets used in this study are daily data obtained from Datastream™, the spot rates for the 9 exchange rates considered and the continuous futures contracts for the other markets Dunis and Miao (2004). For these reasons the time series used in this research are all daily closing data obtained from a historical database provided by Datastream™, as our research benchmark is based on Dunis and Miao (2004) study.

The investigation of our research is based on the London daily closing prices for the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures. The data retained is presented in Table 1 along with the relevant Datastream mnemonics, and can be reviewed in Sheet 1 of the DataAppendix.xls Excel spreadsheet.

Table 1 Data and Datastream mnemonics		
Number	Variable	Mnemonics
1	US \$ TO EURO (WMR) - EXCHANGE RATE	USEURSP
2	LME-Copper, Grade A 3 Months U\$/MT - A.M. OFFICIAL	LCP3MTH
3	IPE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE - U\$/BL	LCRCS00
4	EUREX-EURO BUND CONTINUOUS - SETT. PRICE	GGECS00
5	CME-S&P 500 INDEX CONTINUOUS - SETT. PRICE	ISPCS00

All the series span the period 2nd January 1998 to 31st May 2004, totaling 1660 trading days. The data is divided into two periods: the first period runs 2nd January 1998 to 31st December 2002 (1294 observations) used for model estimation and is classification in-sample. The second period from 2nd January 2003 to 31st May 2004 (366 observations) is reserved for out-of-sample forecasting and evaluation. The division amounts to approximately ¼ of the dataset being retained for out-of-sample purposes.

The summary statistics of the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures for the examined period are presented in Figure 1, highlighting skewness and kurtosis in figure 1.1 to 1.5 appendix 1 and also the Jarque–Bera statistic confirms that the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures series is non-normal at the 99% confidence interval.

The use of financial data in levels in the financial market has many problems, “FX price movements are generally non-stationary and quite random in nature, and therefore not very suitable for learning purposes.” (Mehta, 1995: 191). This is similar with commodities markets. To overcome these problems, the financial time series is transformed into rates of return. Given the price level P_1, P_2, \dots, P_t , the rate of return at time t is formed by:

$$R_t = \left(\frac{P_t}{P_{t-1}} \right) - 1$$

An example of this transformation can be reviewed in Sheet 1 column D of the Double Moving model 10-20 days IPE-BRENT CRUDE OIL.xls Excel spreadsheet, and is also presented in figure 3.01 appendix 3.

An advantage of using a returns series is that it helps in making the time series stationary, a useful statistical property. Formal confirmation that the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures returns series is stationary is confirmed at the 1% significance level by both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test statistics, the results of which are presented in Appendix 2 figure 2.01 to 2.32

The financial time series returns are presented in figure 2.01 to 2.32 appendix 2. Transformations into returns often creates a noisy time series. Formal confirmation through testing the significance of the autocorrelation coefficients reveals that the indices returns series is white noise at the 99% confidence interval, the results of which are presented in figure 2.01 to 2.32 appendix 2. For such series the best predictor of a future value is zero. In addition very noisy data often makes forecasting difficult.

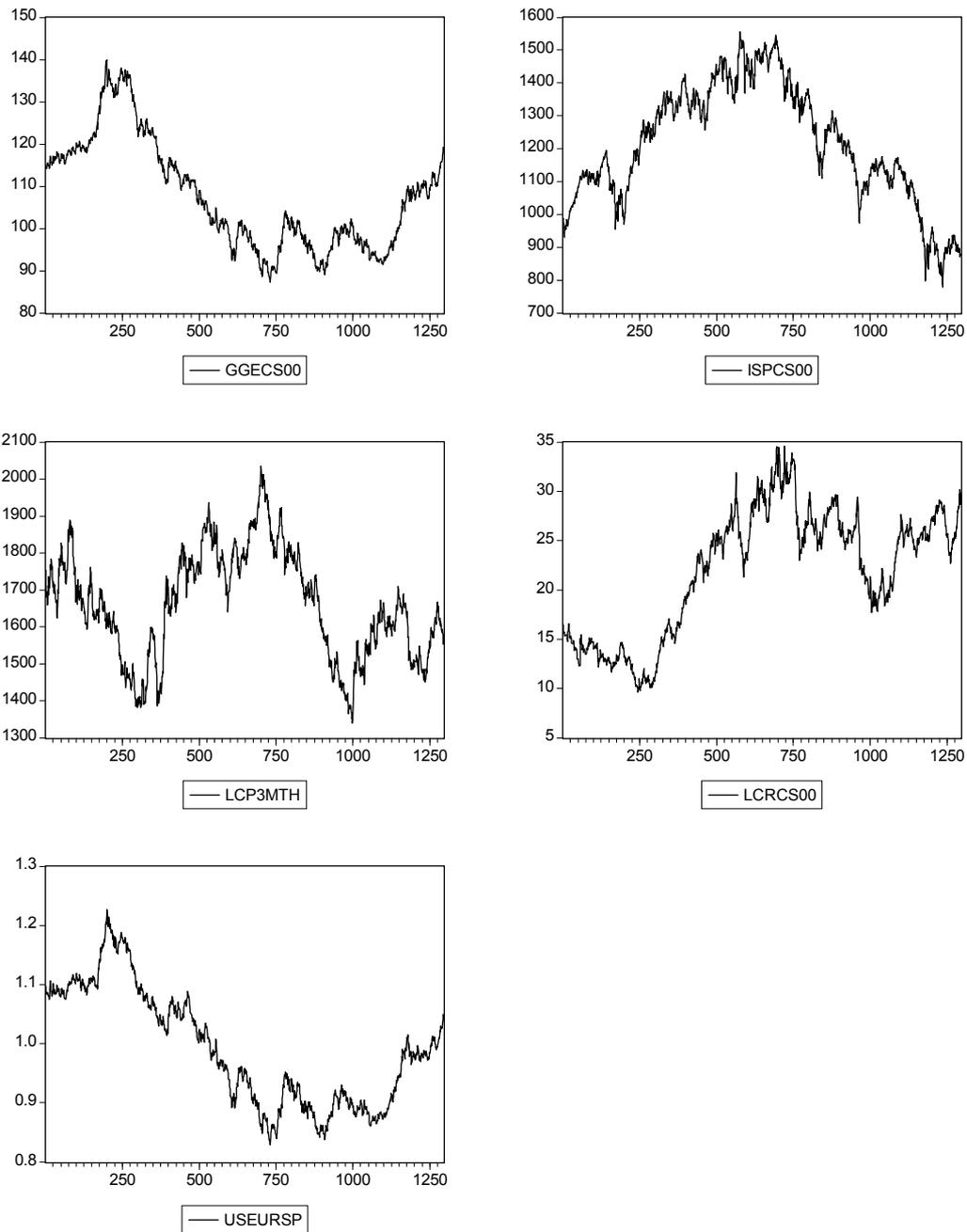


Figure 1

Each index returns summary statistics for the examined period are presented in Appendix 2 figure 2.01 to 2.32. They reveal a slight skewness and high kurtosis and, again, the Jarque–Bera statistic confirms that the Eurex–Euro Bund futures, CME–S&P 500 Index futures, LME–Copper futures, IPE–Brent crude oil futures, EUR/USD series are non-normal at the 99% confidence interval. However, such features are “common in high frequency financial time series data” (Gencay, 1999: 94).

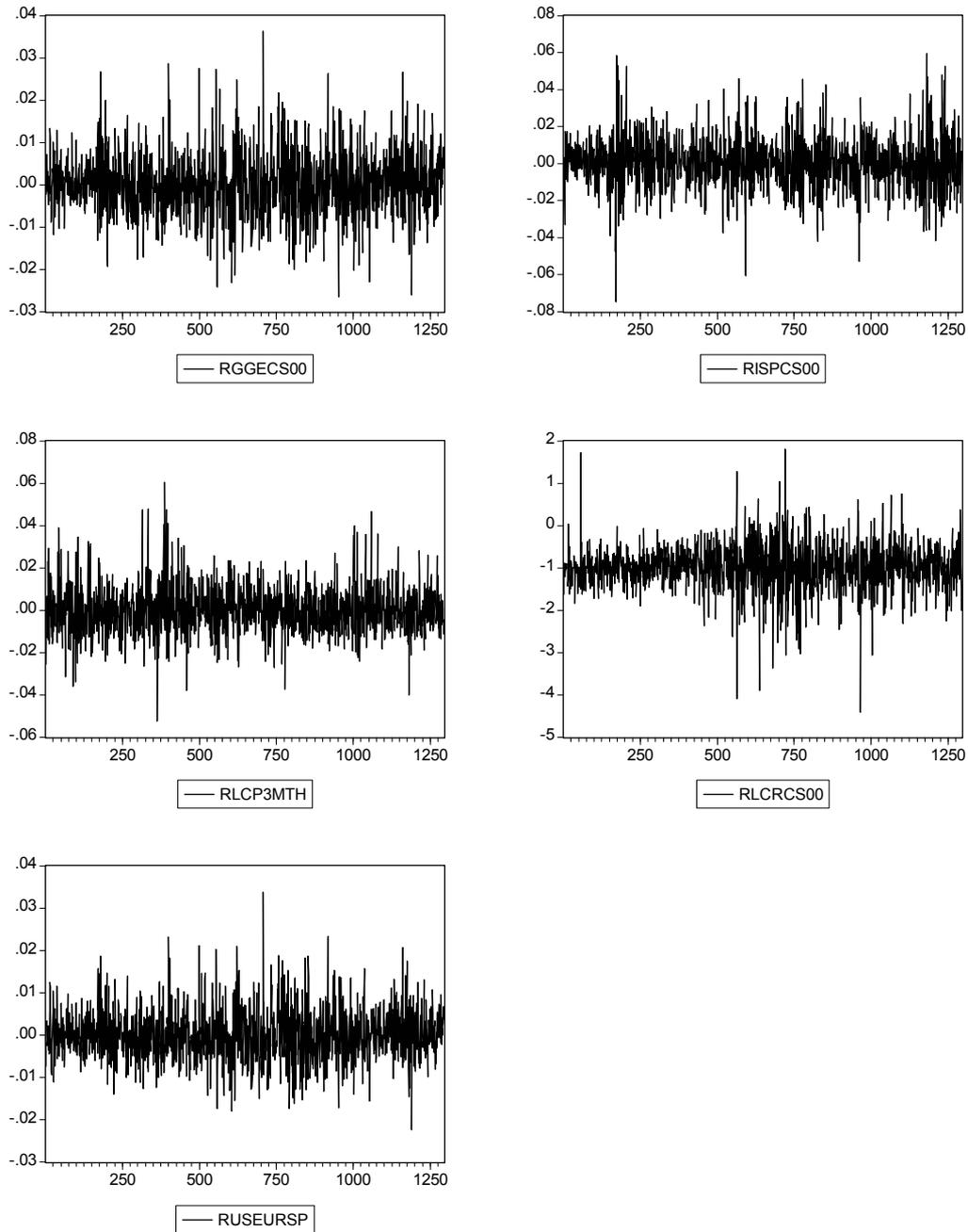


Figure 2

4. Benchmark Models: Theory and Methodology of Dunis and Miao model

The research looks at the performance of technical trading rules on the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 Index futures for last six years, benchmarking previous results done by Dunis and Miao (2004). Their study covers the performance for MACDs with no Filters, with Vol. Filter #1 (No-Trade), and Vol. Filter #2 (Reverse).

Their paper found the optimal trading frequency for different assets by applying technical trading rules, the most widely used forecasting technique in financial markets. In addition they use simple moving average crossover system, using two

volatility filters and a different trading strategy is used high volatility market. They also introduce a model switch strategy where signals from different technical rules are adopted at different levels of market volatility. Their results show (figure 3) that the addition of the two volatility filters and the introduction of a model switch strategy adds value to the model's performance in terms of annualized return, Sharpe ratio and maximum drawdown.

We use their result to benchmark whether using volatility filter and model switch help in getting higher annualized return. Using their, benchmark we use the same sample period to benchmark our results. Arguing in our research that using their model does or doesn't add-value to annualized returns.

Benchmarking Results						
	No Filter		Filter 1		Filter 2	
	Insample	Outsample	Insample	Outsample	Insample	Outsample
Annualised Return	7.53%	9.17%	13.94%	15.26%	17.35%	18.91%
Cumulative Return	31.20%	13.33%	57.76%	22.16%	71.88%	27.47%
Annualised Volatility	8.25%	7.46%	8.48%	8.01%	9.69%	8.90%
Sharpe Ratio	0.91	1.23	1.64	1.90	1.79	2.13
Maximum Daily Profit	2.12%	1.71%	2.36%	1.83%	2.63%	1.88%
Maximum Daily Loss	-2.26%	-1.64%	-2.24%	-1.63%	-2.90%	-1.63%
% Winning trades	53.26%	55.19%	55.27%	55.19%	55.56%	57.10%
% Losing trades	46.74%	44.81%	44.73%	44.81%	44.44%	42.90%
Number of Up Periods	556	202	577	202	580	209
Number of Down Periods	485	162	464	162	461	155
Total Trading Days	1044	366	1044	366	1044	366
Avg Gain in Up Periods	0.40%	0.35%	0.43%	0.42%	0.49%	0.45%
Avg Loss in Down Periods	-0.39%	-0.36%	-0.40%	-0.38%	-0.47%	-0.43%
Avg Gain/Loss Ratio	1.01	0.99	1.05	1.09	1.06	1.05
Profits T-statistics	29.49	23.51	53.12	36.42	19.61	23.29

Figure 3

5. Technical trading rules: THEORY AND METHODOLOGY

In this study we will only focus on Single Moving Average, MACD, Standard Filter rule, Range Break and two forecasting models ARMA and ARMA-Garch models. It is outside the scope of this study to discuss thorough review of all technical trading rules applications including Non Parametric Forecasting Models. However, we have used an automated trading models strategy using in the spreadsheets. Which give the reader the ability to change the Technical Trading rules criteria.

Double Moving Average (DMA)

Double Moving average methods are inexpensive and quick and as a result are routinely used in financial markets. The techniques use an average of past observations to smooth short-term fluctuations. Hanke and Reitsch in their study discuss, "a moving average is obtained by finding the mean for a specified set of values and then using it to forecast the next period"(1998: 143).

The moving average is defined as:

$$M_t = \hat{Y}_{t+1} = \frac{(Y_t + Y_{t-1} + Y_{t-2} + \dots + Y_{t-n+1})}{n}$$

Where M_t is the moving average at time t , n is the number of terms in the moving average, Y_t is the actual level at period t and Y_{t+1} is the level forecast for the next period. The Double Moving Average strategy used is quite simple. Two moving

average series $M_{1,t}$ and $M_{2,t}$ are created with different moving average lengths n and m . The decision rule for taking positions in the market is straightforward. If the short-term moving average intersects the long-term moving average from below a “long” position is taken. Conversely, if the long-term moving average is intersected from above a “short” position is taken.

This strategy can be reviewed in “Double Moving model 10-20 days IPE-BRENT CRUDE OIL.xls” Excel spreadsheet, and is also presented in appendix 3 figure 3.01. Again, please note the comments within the spreadsheet that shows moving average calculations used within the double moving average strategy.

Automated double moving average give us the ability to optimize the best double moving average. The moving averages were used 5, 10, 20, 30, 45, 60 and 90 days. It can be reviewed on the “Double Moving model 10-20 days IPE-BRENT CRUDE OIL.xls” Excel spreadsheet and readers can able to change the averages to see the different results⁵.

The forecaster must use judgement when determining the number of periods n and m on which to base the moving averages. The combination that performed the best over the in-sample period was retained for out-of-sample evaluation. The model selected was a combination of the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 example in appendix 3 figure 3.03 (the result are presented in Appendix 4). A graphical representation of the double moving average is presented in appendix 3 figure 3.02. The performance of this strategy is evaluated in terms of forecasting accuracy via the correct directional change measure, and in terms of trading performance.

Several other “profitable” models results are presented in the Appendix 4. The trading performances of some of these trading rules were only marginally different. Double moving model was significantly profitable in forecasting trading performance for some assets, but for other assets there returns were negative.

Single Moving Average (SMA)

The Single Moving Average is one of the most adaptable and widely used of all technical rules. A moving average shows the average value of observations over a period of time. It is considered quick and inexpensive and as a result it is routinely used in financial markets. The techniques use an average of past observations to smooth short-term fluctuations. When calculating a moving average, an analysis of the observations average value over a predetermined time period is made. As the observations changes, its average price moves up or down. The formula for the traditional moving average is given below:

$$MA_t = \sum_{i=n}^t \frac{P_{t-i}}{N}$$

Where:

price at time $t-n$

⁵ Due to limitation of excel cells and time, it was out of the scope using more then 7 different double moving averages, which requires VBScript macro programming probably giving an edge of deciding any moving average model in any period.

$n = (1, 2, \dots, N)$

p_t price at time t

N = number of days of moving average.

The decision rule for taking positions in the market is straightforward. The trader should go long if $p_t > MA_t$, and the trader should go short if $p_t < MA_t$.

The moving average rule is used to divide the entire sample into either buy or sell periods depending on the relative position of the moving averages. If the short moving- average is above (below) the long, the day is classified as a buy (sell). This rule is designed to replicate returns from a trading rule where the trader buys when the short moving average penetrates the long from below and stays in the market until the short moving average penetrates the long moving average from above (Brock, Lakonishock & LeBaron (1992)).

This strategy can be reviewed in “Moving Model 60 days EUREX-EURO BUND.xls” Excel spreadsheet, and is also presented in appendix 3 figure 3.04. Again, please note the comments within the spreadsheet that shows moving average calculations used within the single moving average strategy.

We use automated single moving average, which gives us the ability to optimize the best simple moving average. The averages were used 5, 10, 20, 30, 45, 60 and 90 days. It can be reviewed in “Moving Model 60 days EUREX-EURO BUND.xls” Excel spreadsheet and readers can change the moving average periods to see its different results⁶.

The performance of best trading rule over the in-sample period was retained for out-of-sample evaluation. The model selection was made for EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 in as example in Appendix 3 figure 3.06 (the result are presented in Appendix 4). A graphical representation of the single moving average is presented in appendix 3 figure 3.05. The performance of this strategy is evaluated in terms of forecasting accuracy via the correct directional change measure, and in terms of trading performance.

Several other “profitable” model results are presented in the appendix 4 were produced and their performances were evaluated. The trading performances of some of these combinations were only marginally different. The simple moving model was significantly adequate in forecasting trading performance for some assets but for other assets there returns were negative.

Filter Rules

Another trading rule, which is one of the most, investigated in the financial literature in the sixties, Alexander (1961, 1964), Fama and Blume (1966) and Dryden (1969)

⁶ Due to limitation of excel cells and time, it was out of the scope using more than 7 different moving averages Requires VBScript macro programming probably giving an edge of deciding any moving average model in any period.

investigated this rules. The filter trading rule is a automatic trading rule which generates a sequence of buy signals and sell signals alternately according to the following rule. Fama and Blume (1966) "Using price history, buy a stock if the price rises x%, hold it until the security falls x%, then sell and go short. Maintain this short position until the price rises x%, then cover the short position and establish a long position"

This strategy can be reviewed in "Filter Rules 90 days LME-Copper.xls" Excel spreadsheet, and is also presented in appendix 3 figure 3.07. Again, please note the comments within the spreadsheet that document periods of calculations used within the Filter Rules strategy.

We use Automated Filter Rule, which gives us the ability to optimize the best Filter Rule Model. The moving averages days were used 5, 10, 20, 30, 45, 60 and 90 days, then the maximum (price rises x%) and minimum (price fall x%). The filter were used of 0.1%, 0.2%, 0.5%, 1.0%, 1.5%, 2.0%, 3.0%, 5.0% on the moving average. It can be reviewed in "Filter Rules 90 days LME-Copper.xls" Excel spreadsheet and readers can change the averages and maximum (price rises x%) and minimum (price fall x%) filter limits to see its trading rule's different returns.

The combination that performed best over the in-sample period was retained for out-of-sample evaluation. The model selected was a combination of the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 example in Appendix 3 figure 3.09 (the result are presented in Appendix 4). A graphical representation of the filter rule is presented in Appendix 3 figure 3.08. The performance of this strategy is evaluated in terms of forecasting accuracy via the correct directional change measure, and in terms of trading performance.

Several other "profitable" model results are presented in the appendix 4 and their performances were evaluated. The trading performances of some of these combinations were only marginally different. The filter model was significantly profitable in forecasting trading performance for some assets but for other assets the returns were negative.

Range Break

Range Break represents key point in time where the forces of supply and demand meet. It is also sometime called support and resistance, where price levels at which movement should stop and reverse direction. This gives a financial analyst a floor and ceiling from which to decide a market strategy.

According to the trading range break rule: A "buy" signal is generated when the price penetrates the "resistance level" defined as the local maximum price A "sell" signal is generated when the price penetrates the "support level" defined as the local minimum price.

The fundamental basis of trading is that the price has difficulties breaking the support level because many investors will anticipate to buy at the minimum price and similarly, price has difficulties breaking through the resistance level because many investors are will anticipate to sell at the maximum price.

This strategy can be reviewed in “Range Break Model 30-75 IPE-BRENT CRUDE OIL.xls” Excel spreadsheet, and is also presented in appendix 3 figure 3.10. Again, please note the comments within the spreadsheet that document periods of calculations used within the range break model strategy.

We use an automated range break model, which gives us the ability to optimise the best range break model. The maximum (resistance) and minimum (support) averages were used 30, 45, 50, 60, 75, 90, 100 days. It can be reviewed in the “Range Break Model 30-75 IPE-BRENT CRUDE OIL.xls” Excel spreadsheet and readers are able to change the maximum (resistance) and minimum (support) averages to see the different returns⁷.

The combination that performed best over the in-sample period was retained for out-of-sample evaluation. The model selected was a combination of the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 example in appendix 3 figure 3.12 (the result are presented in Appendix 4). A graphical representation of the combination is presented in Figure 15. The performance of this strategy is evaluated in terms of forecasting accuracy via the correct directional change measure, and in terms of trading performance.

Several other “profitable” model results are presented in the appendix 4 were produced and their performances were evaluated. The trading performances of some of these combinations were only marginally different. Range Break model was significantly profitable in forecasting trading performance for some assets but for other assets their returns were negative

ARMA Model

An Auto Regressive Moving Average (ARMA) model is created by a process of repeated regression analysis over a moving time window, resulting in a forecast value (Kaufman,1998). ARMA models are particularly useful when information is limited to a single stationary series, and these models are “highly refined curve-fitting devices that use current and past values of the dependent variable to produce accurate short-term forecasts” (Hanke and Reitsch (1998)). The ARMA methodology does not assume any particular pattern in a time-series, but uses an iterative approach to identify a possible model from a general class of models. The ARMA process automatically applies to the most important features of regression analysis in a preset order and continues to reanalyse until an optimum set of parameters is found. If the specified model is not satisfactory, the process is repeated using other models until a satisfactory model is found. Sometimes, it is possible that two or more models may approximate the series equally well, in this case the most parsimonious model should prevail. For a full discussion on the procedure refer to Gouriéroux and Monfort (1995), Pindyck and Rubinfeld (1998).

The ARMA model takes the form:

⁷ Due to limitation of excel cells and time, it was out of the scope using more than 7 different maximum (resistance) and minimum (support) averages, which requires VBScript macro programming probably giving an edge of deciding any moving average model in any period.

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - \dots - w_q \varepsilon_{t-q}$$

where Y_t is the dependent variable at time t
 Y_{t-1} , Y_{t-2} , and Y_{t-p} are the lagged dependent variable
 ϕ_0 , ϕ_1 , ϕ_2 , and ϕ_p are regression coefficients
 ε_t is the residual term
 ε_{t-1} , ε_{t-2} , and ε_{t-p} are previous values of the residual
 w_1 , w_2 , and w_q are weights

Several ARMA specifications were tested on EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500. In particular, several ARMA model were estimated on different assets but few were satisfactory. A satisfactory model being one for which all coefficients are significant at the 95% confidence level (Appendix 3 figure 3.14).

Examination of the autocorrelation function of the error terms reveals that the residuals are random at the 95% confidence level and a further confirmation is given by the correlogram of residuals and serial correlation LM test (appendix 3 figure 3.15 and 3.16).

The model selected was retained for out-of-sample estimation. The performance of the strategy is evaluated in terms of traditional forecasting accuracy and in terms of trading performance. Several adequate models were produced and their performance evaluated, as listed in appendix 4. Ultimately, we picked the model with the best in-sample trading performance and that satisfied the usual statistical tests.

ARMA–Garch Model

Garch models used are used in trading rules in event the ARCH effects. There are several reasons that why we use ARMA-Garch model and forecast. ARMA-Garch are efficient estimators in presence of heteroskedasticity.

Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent, or exogenous variables. ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) originally proposed by Bollerslev (1986) and Taylor(1986) and have become the most popular nonlinear estimation approach used to exploit the autocorrelation characteristics in the underlying squared returns to predict volatility. In its simplest GARCH (1,1) form, the proposed model basically states that the conditional variance of asset returns in any given period depends upon a constant, the previous period's squared random component of the return and the previous period's variance.

Several ARMA specifications were tested on EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500. In particular, several ARMA model were estimated on different assets but few were satisfactory. A satisfactory model being one for which all the coefficients are significant at the 95% confidence level (appendix 3 figure 3.19).

Examination of the autocorrelation function of the error terms reveals that the residuals are random at the 95% confidence level and a further confirmation is given by correlogram of residuals squared and serial correlation LM test (appendix 3 figure 3.20 and 3.21). Ultimately, we picked the model with the best in-sample trading performance that satisfied the above statistical tests

6. Portfolio diversification with equal weighted assets using The Matrix Approach To Portfolio Risk: Theory and Methodology

After getting results using technical trading rules on each asset in appendix 4, we are particularly interested in portfolio return and risk of five assets, when using the best trading rules on each asset. We therefore applied the Markovitz model portfolio returns, which we have discussed in chapter 2. That can be rewritten using matrix notation for more than two asset portfolios. This matrix approach to portfolio risk is discussed by Laws (2003). Modeling portfolio risk within Excel using matrices rather than the linear version of the risk equation appears far more convenient and flexible Laws (2003).

It can be rewritten using matrix notation as:

$$\sigma_p^2 = \begin{bmatrix} w_1 & w_2 \end{bmatrix} \times \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \times \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

If multiply the matrices we will end up with equation. The benefit of using matrix notation is generalize the formula to n -assets as follows:

$$\sigma_p^2 = \mathbf{w}' \Sigma \mathbf{w}$$

where $\mathbf{w} = (w_1, w_2, \dots, w_N)$ and Σ is a covariance matrix with the variance terms on the diagonal and the covariance terms on the off-diagonal. The returns equation can be summarized by:

$$r_p = \mathbf{w}' \boldsymbol{\mu}$$

where $\boldsymbol{\mu}$ is a vector of assets historical returns.

In appendix 3 figure 3.18 we have applied the matrix version of the portfolio risk equation when our portfolio weights are equally distributed. The outcome is the portfolio returns is on figure 4.

	Insample	Outsample
Annualised Return	15.69%	9.48%
Cumulative Return	74.39%	13.26%
Annualised Volatility	12.82%	12.03%
Sharpe Ratio	1.22	0.79
Maximum monthly Profit	3.45%	2.13%
Maximum monthly Loss	-2.23%	-2.42%
Maximum Drawdown	-8.54%	-7.46%
% Winning trades	55.37%	55.46%
% Losing trades	44.63%	44.54%
Number of Up Periods	660	203
Number of Down Periods	532	163
Total Trading Days	1195	367
Avg Gain in Up Periods	0.49%	0.13%
Avg Loss in Down Periods	-0.47%	-0.16%
Avg Gain/Loss Ratio	1.04	0.84
Profits T-statistics	13.40	8.63

Figure 4

7. Empirical Results

Forecasting Accuracy and Trading Simulation

The performance of the strategies needs to be compared, therefore it is necessary to evaluate them on previously unseen data. This situation is likely to be the closest to a true forecasting or trading situation. To achieve this, all models retained an identical out-of-sample period allowing a direct comparison of their forecasting accuracy and trading performance.

Out-of-sample forecasting accuracy and performance measures

The statistical performance measures are often inappropriate for financial applications. Normally, modeling techniques are optimized using a mathematical criterion, but eventually the results are analyzed on a financial criterion upon which it is not optimized. Additionally, the forecasting error may have been minimized during model estimation, but the evaluation of the true merit should be based on the performance of a trading strategy (Dunis and Williams (2002)). Without actual trading, the best means of evaluating performance is via a simulated trading strategy.

The trading performance measures used to analyze the forecasting techniques are commonly used in the fund management industry. Some of the more important measures include the Sharpe ratio, maximum drawdown and average gain/loss ratio. The Sharpe ratio is a risk-adjusted measure of return, with higher ratios preferred to those that are lower, the maximum drawdown is a measure of downside risk and the average gain/loss ratio is a measure of overall gain, a value above one being preferred (Dunis and Jalilov, 2002; Fernandez-Rodriguez *et al.*, 2000). These measures may be a better standard for determining the quality of the forecasts in this application. Because the financial gain from a given strategy depends on trading

performance, not on forecast accuracy. The forecasting accuracy statistics do not provide very conclusive results. The double moving average model has the highest CDC measure, predicting daily changes accurately 60.92% of the time.

Out-of-sample trading performance results of five assets

A comparison of the best trading rules for the five assets used in trading performance results is presented in figure 5, however it was out of the scope of the research to discuss all the results, as there were 104 technical trading models were developed which can be reviewed in appendix 4 (also in result.xls excel sheet). The 60 days single moving model for Euro bund has the lowest downside risk as measured by maximum drawdown at -11.48%. As measured by the probability of a 10% loss the lowest is in coppers futures at 0.53%, however the probability of a 10% loss is 100% in S&P 500 index futures. The Euro bund using single moving average model that predicted the highest number of winning trades at 114. The ARMA model on copper futures has the highest number of transactions at 107, while the double moving model for Brent oil has the second highest at 75. The single moving average strategy has the lowest number of transactions at 21. Similarly, figure 6 and 7 the cumulated gain of 5 assets portfolio using the above stated strategies shows in the graph the evolution of the out-of-sample cumulative gain.

Best Models Results										
	CRUDE OIL		S&P 500 INDEX		EUREX-EURO BUND		LME-Copper		US \$ TO EURO	
	Double Moving 10-20 Insample	Outsample	Insample	ARMA1910 Outsample	Single moving 60days Insample	Outsample	Insample	ARMA237 Outsample	Double Moving 60-90 Insample	Outsample
Annualised Return	23.91%	4.52%	23.92%	1.08%	11.88%	8.01%	12.74%	24.62%	5.99%	9.15%
Cumulative Return	113.38%	6.56%	113.41%	1.57%	56.35%	11.64%	60.42%	35.75%	28.41%	13.30%
Annualised Volatility	36.23%	31.21%	22.92%	14.77%	12.16%	13.92%	17.95%	20.05%	9.66%	9.65%
Sharpe Ratio	0.66	0.14	1.04	0.07	0.98	0.58	0.71	1.23	0.62	0.95
Maximum Daily Profit	13.44%	7.56%	7.47%	3.46%	2.66%	2.82%	6.04%	6.06%	2.07%	1.72%
Maximum Daily Loss	-9.90%	-7.15%	-6.08%	-3.33%	-3.62%	-2.81%	-4.77%	-4.38%	-3.38%	-1.93%
Maximum Drawdown	-55.72%	-24.47%	-16.99%	-16.29%	-11.48%	-13.08%	-48.05%	-45.84%	-13.55%	-7.74%
% Winning Trades	52.26%	49.84%	52.26%	50.71%	52.60%	52.89%	50.82%	54.65%	52.49%	52.02%
% Losing Trades	47.74%	50.16%	47.74%	49.29%	47.40%	47.11%	49.18%	45.35%	47.51%	47.98%
Number of Up Periods	567	157	602	178	627	192	587	194	579	167
Number of Down Periods	518	158	550	173	565	171	568	161	524	154
Number of Transactions	217	75	124	25	61	21	447	107	84	22
Total Trading Days	1195	366	1195	366	1195	366	1195	366	1195	366
Correct Directional Change	60.92%	55.74%	51.46%	47.54%	57.57%	58.20%	51.80%	61.75%	53.47%	49.18%
Avg Gain in Up Periods	1.84%	1.64%	1.16%	0.73%	0.60%	0.68%	0.91%	0.97%	0.48%	0.54%
Avg Loss in Down Periods	-1.79%	-1.58%	-1.06%	-0.74%	-0.57%	-0.69%	-0.84%	-0.94%	-0.48%	-0.50%
Avg Gain/Loss Ratio	1.03	1.03	1.09	0.98	1.06	0.98	1.09	1.02	1.01	1.08
Probability of 10% Loss	7.62%	19.64%	26.79%	100.00%	0.21%	1.11%	16.35%	0.53%	4.73%	41.77%
Profits T-statistics	22.81	2.77	36.08	1.40	33.78	11.01	24.54	23.49	21.44	18.15

Figure 5

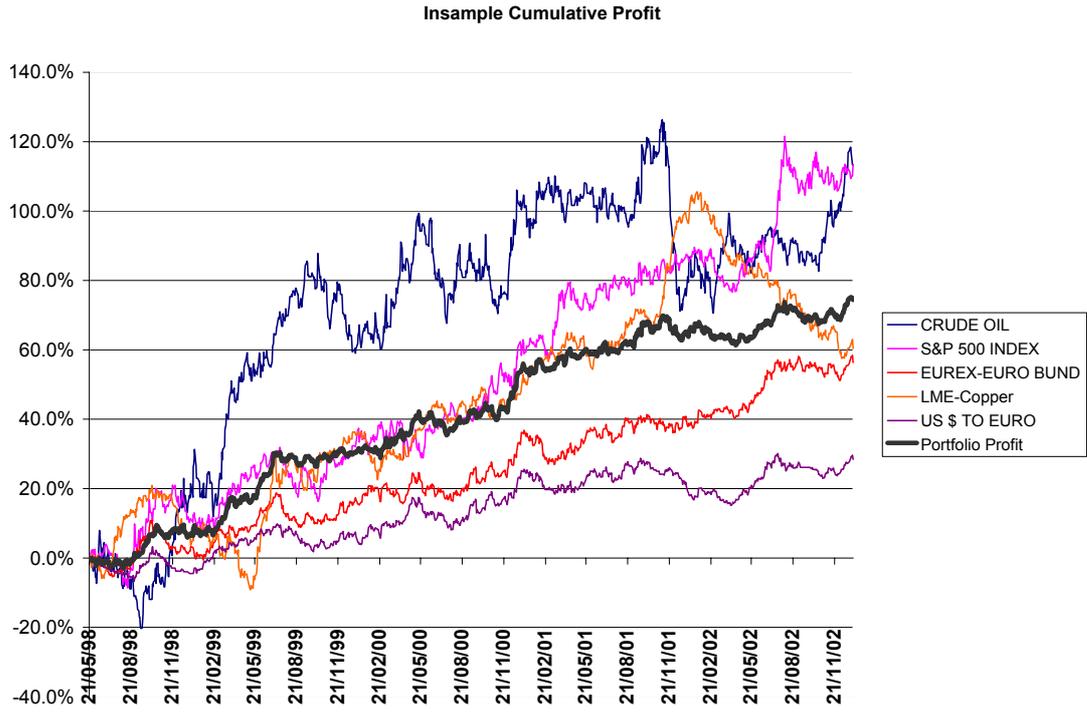


Figure 6

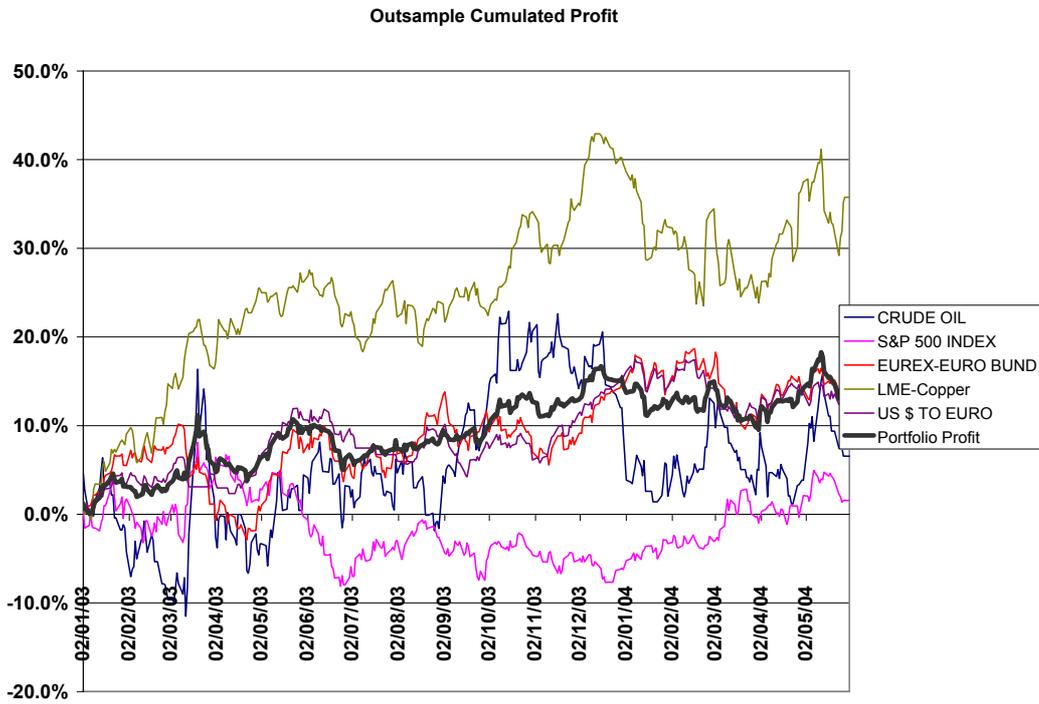


Figure 7

Out-of-sample trading performance results of portfolio with benchmarking models

The comparison of portfolio results and benchmarking result are in figure 8. Our portfolio results marginally outperform the benchmark strategy of Dunis and Miao “No filter”, with an annualized return of 9.48% and a cumulative return of 13.6%, and in terms of risk-adjusted performance with a Sharpe ratio of 0.79, was approximately half of benchmark result. These results fail to out-perform with Dunis and Miao “filter 1 and 2” strategies model. In our study, the transaction cost was not realized as the benchmark model results exclude the cost.

Benchmarking Results								
	Our Results		No Filter		Filter 1		Filter 2	
	Insample	Outsample	Insample	Outsample	Insample	Outsample	Insample	Outsample
Annualised Return	15.69%	9.48%	7.53%	9.17%	13.94%	15.26%	17.35%	18.91%
Cumulative Return	74.39%	13.26%	31.20%	13.33%	57.76%	22.16%	71.88%	27.47%
Annualised Volatility	12.82%	12.03%	8.25%	7.46%	8.48%	8.01%	9.69%	8.90%
Sharpe Ratio	1.22	0.79	0.91	1.23	1.64	1.90	1.79	2.13
Maximum Daily Profit	3.45%	2.13%	2.12%	1.71%	2.36%	1.83%	2.63%	1.88%
Maximum Daily Loss	-2.23%	-2.42%	-2.26%	-1.64%	-2.24%	-1.63%	-2.90%	-1.63%
% Winning trades	55.37%	55.46%	53.26%	55.19%	55.27%	55.19%	55.56%	57.10%
% Losing trades	44.63%	44.54%	46.74%	44.81%	44.73%	44.81%	44.44%	42.90%
Number of Up Periods	660	203	556	202	577	202	580	209
Number of Down Periods	532	163	485	162	464	162	461	155
Total Trading Days	1195	367	1044	366	1044	366	1044	366
Avg Gain in Up Periods	0.49%	0.13%	0.40%	0.35%	0.43%	0.42%	0.49%	0.45%
Avg Loss in Down Periods	-0.47%	-0.16%	-0.39%	-0.36%	-0.40%	-0.38%	-0.47%	-0.43%
Avg Gain/Loss Ratio	1.04	0.84	1.01	0.99	1.05	1.09	1.06	1.05
Profits T-statistics	13.40	8.63	29.49	23.51	53.12	36.42	19.61	23.29

Figure 8

8. Conclusion

This study investigated the use of different technical trading models in forecasting and trading the EUR/USD, LME-Copper futures, IPE-Brent crude oil futures, Eurex-Euro Bund futures, CME-S&P 500 futures index. Further, we used these technical trading strategies to build an equally weighted portfolio. The performance was measured statistically and financially using a trading simulation and benchmark with Dunis and Miao (2004) trading strategy models. The reason behind the trading simulation is, if profit from a trading simulation is compared solely on the basis of statistical measures, the optimum model from a financial perspective would rarely be chosen.

However, our portfolio has 9.48% annual return and 13.26% cumulated profit, which are significantly different from Dunis and Miao. Suggesting, that the volatility filter rules used by Dunis and Miao in “volatility filter 1 and filter 2” strategies are profitable and provide returns, which add on value to trading performance and forecasting ability.

Interestingly, it is worth noting that the models winning trades accuracy was marginally different from benchmark models. Overall our results confirm the credibility and potential of technical trading models and particularly when comparing with Dunis and Miao (2004) in “filter 1 and filter 2” models as a benchmark. While their models offer a promising trading technique, further investigation into their models is possible, or into combining forecasts. Many researchers agree that individual forecasting methods are mis-specified in some manner, suggesting that combining multiple forecasts leads to

increased forecast accuracy (Dunis and Huang, 2002). Despite the limitations and potential improvements mentioned above, our results strongly suggest that Dunis and Miao (2004) using volatility “filter 1 and filter 2” can add value to the forecasting process. Their model clearly outperforms the more traditional modeling techniques analyzed in this research.

Reference

Acar, E. and Lequeux, P. (1995), “Trading rule profits and the underlying time series properties”, *First International Conference on High Frequency Data in Finance*, Zurich, Switzerland.

Acar, E. and Lequeux, P. (1996), “*Dynamic strategies, a correlation study*”, in Dunis eds, *Forecasting Financial Markets*, Wiley, 93–123.

Andreou, E., Pittis, N and Spanos.A (2001), “On Modelling Speculative Prices: The Empirical Literature”. *Journal of Economic Surveys*, April, Vol.15, No2, pp.187-220.

Alexander, S. (1961), “Price Movements in Speculative Markets: Trends or Random Walk”, *Industrial Management Review*, 2, pp.7-26.

Alexander, S. (1964), “Price Movements in Speculative Markets: Trends or Random Walk”, No.2, *Industrial Management Review*, 5, pp.338-372.

Baldrige, J., Meath B, and Myers, H. (2000), “Capturing Alpha through Active Currency Overlay.”, *Frank Russell Research Commentary*, May 2000.

Brock, W., Lakonishok, J. and LeBaron, B. (1992), "Simple Technical Rules and the Stochastic Properties of Stock Returns", *Journal of Finance*, 47, 1731-1764.

Bollerslev, T. (1986), "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics*, Vol. 31, , 307-28.

Bachelier, L. (1900), *Theorie de la Speculation* (Thesis), *Annales Scientifiques de l'Ecole Normale Supérieure*, II I -17, 21-86. (English Translation;- Cootner (ed.), (1964) *Random Character of Stock Market Prices*, Massachusetts Institute of Technology pp17-78 or Haberman S. and Sibett T. A. (1995) (eds.), *History of Actuarial Science*, VII, 15-78. London)

Dryden, M. (1969), “A Source of Bias in Filter Tests of Share Prices.”, *Journal of Business*, 42,321-325

Dunis, C. (1989), “Computerised Technical Systems and Exchange Rate Movements”, chapter 5, 165-205, in C. Dunis and M. Feeny [eds.], *Exchange Rate Forecasting*, Probus Publishing Company, Cambridge, UK.

Dunis, C. and Williams, M. (2002), "Modelling and Trading the EUR/USD Exchange Rate: Do Neural Network Models Perform Better?", *Derivatives Use, Trading and Regulation*, **8**, 211-239.

Dunis, C. Huang, X. (2002), "Forecasting and trading currency volatility: an application of recurrent neural regression and model combination", *Journal of Forecasting*, Volume 21, Issue 5, 2002. Pages 317-354

Dunis, C. and Miao, J. (2004), "Optimal Trading Frequency for Active Asset Management: Evidence from Technical Trading Rules", (forth coming in *Journal of finance*) currently available at www.cibef.com

Fama, E. and Blume, M. (1966), "Filter Rules and Stock Market Trading", *Journal of Business*, 40, pp.226-241.

Fama, E. (1970), "Efficient Capital Markets: A review of Theory and Empirical Work", *Journal of Finance*, 25, pp.383-417.

Fernandez-Rodriguez, F., C. Gonzalez-Martel and S. Sosvilla-Rivero (2000), "On the Profitability of Technical Trading Rules Based on Artificial Neural Networks: Evidence from the Madrid Stock Market", *Economics Letters*, **69**, 89–94.

Gencay, R. (1999), "Linear, Non-linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules", *Journal of International Economics*, 47, 91–107.

Grubel, H. (1968), "Internationally Diversified Portfolios: Welfare Gains and Capital Flows", *American Economic Review*, 59(5), 1299-1314.

Gouriéroux, C. and Monfort, A. (1995), *Time Series and Dynamic Models*, translated and edited by G. Gallo, Cambridge University Press, Cambridge.

Hudson, Robert., Micheal Dempsey, and Kevin 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*, pp. 1121-1132.

Hanke, J. E. and Reitsch, A. G. (1998), *Business Forecasting*, 6th edition, Prentice-Hall, New Jersey.

Isakov, D. & Hollistein, M., 1998. "Application of Simple Technical Trading Rules to Swiss Stock Prices: Is It Profitable?," Papers 98.2, *Ecole des Hautes Etudes Commerciales*, Universite de Geneve

Kaastra, I. and M. Boyd (1996), "Designing a Neural Network for Forecasting Financial and Economic Time Series", *Neurocomputing*, 10, 215–236.

Kwon, K.Y. and Kish, R. J. (2002), "Technical trading strategies and return predictability: NYSE", *Applied Financial Economics*, vol. 12, no. 9, pp. 639-653(15)

Laws, J. (2003), "Portfolio Analysis Using Excel", *Applied Quantitative Methods for Trading and Investment*. Edited by C. Dunis, J. Laws and P. Na ým, John Wiley & Sons, Ltd

Levich, R. and Thomas, L. (1993), "The Significance of Technical Trading Rule Profits in the Foreign Exchange Markets: A Bootstrap Approach". *Journal of International Money and Finance* 12 451-474.

Lukac, L. P., and Brorsen, B.W. (1990), "A Comprehensive Test of Futures Market Disequilibrium", *The Financial Review*, 25, 593-622.

Markowitz, H. (1952), "Portfolio Selection", *Journal of Finance*, 7, 77-91.

Mehta, M. (1995), "Foreign Exchange Markets", in A. N. Refenes (ed.), *Neural Networks in the Capital Markets*, John Wiley, Chichester, pp. 176–198.

Menkhoff, L (1997), "Examining the use of technical currency analysis", *International Journal of Finance and Economics*, 2:4, 307-318.

Perry J. Kaufman (1998), " *Trading System and Methods*", (3rd Edition, John Wileys & Sons), pp.55-60.

Pindyck, R. S. and Rubinfeld, D. L. (1998), "*Econometric Models and Economic Forecasts*", 4th edition, McGraw-Hill, New York.

Pruitt, S.W. and White, R.E. (1988), "The CRISMA trading system: who says technical analysis can't beat the market?", *Journal of Portfolio Management*, 14, 55-58.

Strange, B. (1998), "Currency Overlay Managers Show Consistency", *Pensions and Investments*

Taylor, M. P. and Allen, H. (1992), "The Use of Technical Analysis in the Foreign Exchange Market", *Journal of International Money and Finance*, 11, 304-314.

Taylor S.J. (1986), *Modelling Financial Time Series*, New York, Wiley.

Tobin, J. (1958), "Liquidity Preference as Behaviour Towards Risk", *The Review of Economic Studies*, 25(67), 65-86

Yochanan, S., Uri, B., Paul, K. and Joseph, Y. (2001), "A Moving Average Comparison of the Tel-Aviv 25 and S&P 500 stock Indexes", *Penn CARESS Working Papers, UCLA Department of Economics*.