JMU

School of Accounting, Finance and Economics
Faculty of Business and Law
Liverpool John Moores University

Volatility Filters for Active Asset Trading and Portfolio Optimisation

Jia Miao

LIVER... SITY

A Thesis submitted in partial fulfilment of the requirements of Liverpool John Moores University for the degree of **Doctor of Philosophy**

May 2006

DECLARATION

This is to certify that this thesis is the result of an original investigation. The material has not been used in a submission for any other qualification. Full acknowledgement has been given to all sources used.

Candidate

....
(Signature)

Director of Studies

....
(Signature)

COMMITTEE

SUPERVISORY TEAM

Prof. Christian Dunis	(Director of Studies)
Jason Laws	

EXAMINATION TEAM

Prof. John Thompson	(Internal Examiner)
Prof. Eric Girardin	(External Examiner)

ACKNOWLEDGEMENT

First and foremost, I would like to thank my director of studies, Prof. Christian Dunis for his valuable guidance, criticism and support. I am truly grateful to my second supervisor, Jason Laws, for his comments, inspiration and support throughout. I would also like to thank Dr. Swee Leong for his advices on spectral analysis.

Many thanks, also to Andreas and Ben, to students from various MSc International Banking and Finance classes and other colleagues at Liverpool John Moores University.

Finally, I would like to thank school of Accounting, Finance and Economics at Liverpool John Moores University for its continued financial support. In particular, I would like to thank the head of the school, Dave Gardner, Christina Sargant, Prof. Ken Holden and Stephen Smith.

ABSTRACT

Technical trading rules have been used in financial markets for decades, and are still one of the most popular forecasting techniques in financial markets. Among these, technical trending systems are quite popular, but are known to perform poorly in volatile markets. In addition, the presence of transaction costs in the financial markets is an important factor in making investment decisions. For both active asset trading and dynamic portfolio optimsation, the benefits from switching market positions at very high frequency may hardly compensate for the transaction costs incurred.

The primary motivation of the thesis is to explore and utilise the relationships between underlying volatilities and technical trending rules as well as other alternative trading strategies. What is more, the existence of international contagion among major financial markets suggests a covariance matrix regime change between "normal", i.e. quiet times and times of financial instability. This provides an opportunity to introduce a rebalancing scheme where the dynamic portfolio is only rebalanced when the underlying volatility regime changes.

The major contribution of this thesis is to investigate the performance of different trading strategies in different volatility regimes. The thesis then proposes the use of volatility filters to enhance the performance of these trading strategies. In addition, the thesis also develops a dynamic portfolio optimisation scheme where the underlying market volatility functions as a timing device for portfolio reallocation and the portfolio is only rebalanced when the underlying volatility regime changes.

In conclusion, some of the most widely used trading strategies are found to perform poorly when the markets are highly volatile, and adaptive strategies like the volatility filters proposed in this thesis should be adopted during such periods to enhance trading performance. In addition, correlations between

international financial markets change significantly with changes in these markets volatility regimes. Volatility filters based on these volatility regime changes can play as an effective timing device for dynamic portfolio optimisation.

TABLE OF CONTENTS

Chapter 3

Chapter 4

PART TWO
Volatility Filters for Alternative Trading Rules

Chapter 5

Chapter 6

PART THREE
Volatility Filters for Dynamic Portfolio Optimisation

Chapter 7

Chapter 8

LIST OF TABLES

Chapter 6

Chapter 7

Appendix

LIST OF FIGURES

CHAPTER 1

General Introduction

1.1 Scope

While numerous techniques have been proposed to forecast financial markets, they fall into two main categories: fundamental analysis and technical rules. Compared to most fundamental quantitative methods which require financial variables to be transformed to stationary series first, technical trading rules are generally applied directly to the price level. In addition, while the process of finding the right parameters for fundamental models can be both cumbersome and indecisive, there are several technical trading rules parameters which are commonly accepted by market practitioners and have been proven to perform well. It is for these reasons that technical trading rules have been used in financial markets for decades, and are still one of the most popular forecasting techniques in financial markets. Billingsley and Chance (1996) mention that 70% of the Commodity Trading Advisors (CTAs) are trend followers and tend to trade in a similar manner. The strategies proposed based on technical trading rules which partially replicate the behaviour of investors can thus have both academic and industry significance.

However, financial markets are not always moving in trends which are just one of the basic elements of price movement, the other being range trading situations or cycles. As a matter of fact, Hurst (1997) notes that 23% of all price motion is oscillatory in nature. If this assumption is true, there is no reason to trade solely on the basis of technical trending rules at all times and it is important to identify market cyclical properties and to trade accordingly when the underlying markets display strong cyclical properties. In addition, the rejection of the simple risk-neutral efficient market hypothesis in the foreign exchange (FX) market opens the possibility of the profitable use of a carry model taking full advantage of interest rate differentials to trade currencies. Largely known (and implemented) as "carry trading" by currency fund managers, this carry strategy entails to always hold the high yield currency and short the corresponding low yield currency in a currency pair.

Market volatility has an impact on trading, for instance, Pan *et al.* (2003) study the influence of volatility on futures trading and find that an increase in volatility motivates traders to engage in more trading in futures markets. It is also well known that trend-following systems perform poorly when markets become volatile and volatility filters have been proposed to improve the overall performance of these systems. Roche and Rockinger (2003) explain that high volatility periods often correlate with periods when prices change direction, and therefore propose to reverse the technical signals generated when market volatility is forecast to be higher than a chosen threshold. Dunis and Chen (2005) argue that moving average convergence and divergence (MACD) models perform poorly in volatile markets, precisely because volatile markets imply frequent direction changes, and thus introduce a volatility filter which stops trading at times of high volatility. Apart from technical trending rules, there is no academic study on whether underlying volatility regimes have similar impacts on other alternative trading strategies that are commonly adopted by market practitioners, such as the carry trading strategy in the foreign exchange markets.

Many now accept that financial markets are inefficient to some extent, and the presence of transaction costs is another important factor in making investment decisions. Most financial modelling techniques require large numbers of observations to keep the model statistically efficient. Statistically this requires models use frequent data at least on a daily frequency, which in turn generates daily forecasts and signifies market position changes at almost the same high frequency. But practically, in some markets, trading on daily basis is not feasible simply because of transaction costs. In a word, although the statistical nature of most forecasting techniques requires data to be at high frequency, real world trading in financial markets is a longer term decision. From the perspective of portfolio optimisation, although the success of modelling the so-called conditional variance and covariance makes it possible to optimise portfolios dynamically with an updated forecast of the covariance matrix, the question is whether a dynamic rebalancing scheme accounting for the variability of the covariance matrix can outperform a portfolio with constant weights after transaction costs are deducted.

1.2 Motivations

Therefore, the motivations of this thesis are as follows.

Firstly, technical trading rules are one of the most popular forecasting techniques in financial markets. Among these, technical trending systems are quite popular, but are known to perform poorly in volatile markets, which suggests that adaptive strategies should be used during these volatile periods. In addition, financial markets are not always moving in trends and alternative trading strategies adopted by market practitioners can also be affected by the level of underlying market volatilities. It is therefore important to explore and utilise the relationships between underlying volatilities and different trading strategies.

Secondly, the presence of transaction costs makes the trading frequency or holding period an important factor in determining investment strategies. Although the holding period is seen as an important factor affecting financial decisions, there are no articles, to the best of our knowledge, focused on finding the optimal holding period for active asset management. With technical trading rules using daily or more frequent data, different trading frequencies or holding periods can be achieved with the selection of parameters and possibly with the addition of certain filters.

Thirdly, dynamic portfolio rebalancing utilizing conditional variance and covariance matrices involves a frequent modification of asset weights, thus the benefits from dynamic rebalancing can be quickly erased by transaction costs. The existence of international contagion among major financial markets suggests a covariance matrix regime change between "normal" times and times of financial instability. This provides an opportunity to introduce a rebalancing scheme where the dynamic portfolio is only rebalanced when the underlying volatility regime changes.

1.3 Contributions to Knowledge

The contribution of the thesis can be broken down into three areas.

Firstly, the thesis investigates the performance of trend-following moving average convergence and divergence (MACD) systems in different volatility regimes and proposes volatility filters to enhance performance. Based on the performance of such trending systems which are commonly used by market practitioners, the thesis identifies the optimal trading frequency for different assets in the context of active asset management.

Secondly, the thesis explores whether alternative trading strategies behave differently in volatile markets. Specifically, the thesis studies the performance of a simple passive carry model in periods of different volatility regimes and justifies the use of volatility filters applied to the carry model. Moreover, the thesis studies the existence of cyclical properties in foreign exchange markets with the use of spectral analysis. The thesis then proposes confirmation filters on a trading model based on spectral analysis.

Finally, the thesis develops a dynamic portfolio optimisation scheme where the underlying market volatility functions as a timing device for portfolio reallocation and the portfolio is only rebalanced when the underlying volatility regime changes. In addition, the traditional Markowitz mean variance (MV) optimisation can lead to an "inefficient frontier" with wrong expected returns.

The thesis also proposes a risk-adjusted expected return (RAER) approach where expected returns are expressed as a linear function of the risk incurred through a risk-aversion coefficient.

1.4 Structure

The thesis is composed of three parts: in the first part (chapters 2, 3 and 4), we start to investigate the performance of trend-following systems in different volatility regimes, and then propose volatility filters to improve trading performance of such systems. We also compare the performance of these volatility filters using alternative volatility forecasts. In the second part (chapters 5 and 6), we apply the volatility filters proposed to alternative trading models other than trend-following systems. In the third part (chapter 7), volatility filters are further extended to asset allocation, where volatility regime changes are used as a timing device to optimise portfolio rebalancing. Investigating and evaluating alternative filter rules in asset management being the main "theme line" of the thesis, each chapter also has its own objective. Each of these chapters represents a distinct academic paper and thus includes sections covering literature, methodology, empirical application and conclusion.

More specifically, in chapter 2, we investigate the performance of trend-following MACD systems in different volatility regimes. We then propose volatility filters, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals are reversed in volatile periods. We also introduce a model switch strategy where signals from different technical rules are adopted at different levels of market volatility. Our results show that the addition of the two volatility filters and the introduction of a model switch strategy add value to the MACD models studied. Finally, we investigate the optimal trading frequency for active tradings in futures and currency markets.

In chapter 3, we relate the findings from chapter 2 to the real world business: two portfolios, which are highly correlated with a managed futures index and a currency traders' benchmark index are formed to replicate the performance of typical managed futures and managed currency funds. We then study whether the addition of volatility filters can improve the performance of these two portfolios with the hope that the proposed techniques will then have both academic and industrial significance.

In chapter 4, moving from the previous 2 chapters where RiskMetrics is used to measure market volatility and volatility filters, we investigate whether alternative volatility forecasts can further improve models performance with the proposed volatility filters.

In chapter 5, we investigate whether a simple passive carry model can outperform a typical currency fund manager replicated by dynamic MACD models. We further investigate the performance of the carry model in different volatility regimes and study whether the addition of volatility filters can also improve the carry model performance.

In chapter 6, we study the existence of cyclical properties in foreign exchange markets with the use of spectral analysis. Inspired by findings from previous chapters, we also study whether the performance of the spectral model is affected by different market volatility regimes. Finally, we study the economic value of a trading model based on spectral analysis compared with benchmark technical trending MACD models in the FX markets.

In chapter 7, we propose a dynamic rebalancing scheme utilizing the underlying market volatility which functions as a timing device for portfolio reallocation and the portfolio is only rebalanced when the underlying volatility regime changes. In addition, the traditional Markowitz mean variance optimisation can lead to an "inefficient frontier" with wrong expected returns. We propose a risk-adjusted expected return (RAER) approach where expected returns are expressed as a linear function of the risk incurred through a risk-aversion coefficient.

Finally, chapter 8 concludes the dissertation, followed by an appendix and references.

The thesis has already generated 6 academic papers, all of which have been published, presented at international conferences or accepted for publication in refereed academic journals:

Chapter 2: "Optimal Trading Frequency for Active Asset Management: Evidence from Technical Trading Rules" has been

- Presented at the *Forecasting Financial Markets Conference* held in Paris 4^{th} – 6^{th} of June 2004.

- Published by the *Journal of Asset Management*, 2005, 5, 305-326.

Chapter 3: "Volatility Filters for Asset Management: An Application to Managed Futures" has been

- Accepted by the *Journal of Asset Management*, forthcoming.

Chapter 4: "Volatility Filters for FX Portfolios Trading: The Impact of Alternative Volatility Models" has been

- Accepted by the *Applied Financial Economics Letters*, forthcoming.

Chapter 5: "Trading Foreign Exchange Portfolios with Volatility Filters: The Carry Model Revisited" has been

- Accepted by the *Applied Financial Economics*, forthcoming.

Chapter 6: "Advance Frequency and Time Domain Filters for Currency Portfolio Management" has been

- Accepted by the *Journal of Asset Management*, forthcoming.

Chapter 7: "Volatility Filters for Dynamic Portfolio Optimisation" has been

- Presented at the *Forecasting Financial Markets Conference* held in Marseilles 1st – 3rd of June 2005.
- Published by the *Applied Financial Economics Letters*, 2005, 1, 111-119.

1.5 Performance Evaluation

Traditional statistical performance measures are not appropriate for financial applications simply because the model with minimum forecasting errors in statistical term does not necessarily guarantee maximised trading profits, which is often deemed as the ultimate objective of a financial application. The best way to evaluate alternative financial models is therefore to evaluate their trading performance by means of a trading simulation. In this thesis, the following trading performance measures are used.

The asset return r_t at time t is calculated as the percentage change of the underlying asset price p. The cumulative return r_c is the overall return for a certain period of time studied.

$$r_t = (\frac{p_t - p_{t-1}}{p_{t-1}}) \tag{1.1}$$

$$r_c = \sum_{t=1}^{n} r_t \tag{1.2}$$

The cumulative return is usually annualised as the annualised return r_a. The risk exposure measured by the standard deviation is transformed to the annualised volatility σ_a in a similar way. For annualised measures, m=252 for daily data, m=52 for weekly data and m=12 for monthly data.

$$r_a = m * (1/n) \sum_{t=1}^{n} r_t \tag{1.3}$$

$$\sigma_a = \sqrt{\frac{m * \sum_{t=1}^{n} (r_t - \bar{r})^2}{n-1}} \tag{1.4}$$

Under the standard deviation approach of measuring risk exposure, both upside and downside volatility are penalised in the same way. In reality, a fund manager is mostly concerned with the downside risk. The maximum drawdown (MD) measures the maximum downside risk a certain trading strategy can suffer if the investor enters the market at the worst time.

$$MD = Min\left[r_t - Max\left(\sum_{t=1}^{n} r_t\right)\right] \tag{1.5}$$

Higher returns are usually associated with higher risks, and the evaluation of models' performance can be biased if assessed merely on the basis of return. The risk-adjusted information ratio (IR) is a measure dealing with the trade-off between risk and return.

$$IR = \frac{r_a}{\sigma_a} \tag{1.6}$$

PART ONE

Volatility Filters for Technical Trading Rules

CHAPTER 2

Optimal Trading Frequency for Active Asset Management: Evidence from Technical Trading Rules

Chapter Overview

Despite the fact that technical trending rules have long been applied in financial markets, these rules are known to perform poorly when the underlying markets are highly volatile. The primary motivation of this chapter is to study whether the addition of volatility filters adds value to the performance of these trading rules. In addition, the presence of transaction costs makes trading frequency or holding period an important factor in determining investment strategies. With the study of technical trading rules, this chapter attempts to identify the optimal trading frequency for different assets in the context of active asset management.

Two volatility filters were proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from the original trading strategies are reversed if market volatility is higher than a given threshold. Our results show that the addition of the two volatility filters has significantly improved the performance of trend-following MACD systems at both the single asset and portfolio level.

2.1 Introduction

Most financial modelling techniques require large numbers of observations to keep the model statistically efficient. This suggests that models should use more frequent data, which in turn generates forecasts and implies market position changes at almost the same high frequency. But practically, in some markets, trading on a high-frequency basis is not feasible simply because of transaction costs. Transaction costs are less crucial in foreign exchange (FX) markets where transaction costs are quite low, but they become a more important factor when investing in markets like the stock and bond markets, where the benefits from switching market positions at almost daily frequency can hardly compensate for the transaction costs incurred.

Active asset management then involves a holding period longer than a daily frequency. While being neglected in the academic literature, the so-called optimal trading frequency is important in making practical investment decisions. In the case of active asset management, the optimal trading frequency or holding period, which determines a specific trading strategy (possibly with certain cut-off points identified), represents how actively / frequently investors should trade to maximize post-transaction-cost profits.

In a word, although the statistical nature of most financial series requires high frequency data, real world financial investment is a longer term decision. Therefore investing in financial markets involves answering the following question: how long is the optimal holding period for active asset management or, more specifically, how frequently should a specific financial asset be traded?

While numerous techniques have been proposed to forecast financial markets, they fall into two main categories: fundamental analysis and technical rules. Most fundamental quantitative methods require financial variables to be transformed to stationary series first, whereas technical trading rules are generally applied directly to the price level. In addition, while the process of finding the right parameters for fundamental models could be both cumbersome and indecisive, there are several technical trading rules parameters that are commonly accepted by market practitioners, which have been proven to perform well. Moreover, with trading rules using daily or more frequent data, different trading frequencies can be achieved with the selection of parameters and possibly with the addition of certain filters. Finally, technical trading rules have been used in financial markets for decades, and are still one of the most popular forecasting techniques in financial markets. Studying the performance of technical trading rules can thus partially replicate the behaviour of investors, and the optimal trading frequency derived from the study of technical trading rules can be a valuable and meaningful input, especially to those who rely on technical rules for making investment decisions.

Therefore, the motivation of this chapter is as follows. Firstly, despite the fact that technical trending rules have long been applied in financial markets, these rules are known to perform poorly when the underlying markets are highly volatile. Continuing previous studies on technical trading rules, we study whether the addition of volatility filters adds value to the performance of these rules. Observing the inconsistent performance of different technical rules at different levels of market volatility, we also introduce a model switch strategy, where technical trading rules are selected based on the level of intrinsic market volatility.

Secondly, many now accept that financial markets are inefficient to some extent, and the presence of transaction costs makes the trading frequency or holding period an important factor in determining investment strategies. Although the holding period is seen as an important factor affecting financial decisions, there are no articles, to the best of our knowledge, focused on finding the optimal trading frequency or holding period for active asset management.

Thirdly, albeit less importantly, technical trading rules have been heavily studied in stock markets and FX markets, and less attention has been made to commodity and bond markets. In this chapter, we apply technical rules to a wide variety of financial assets. Furthermore, we also investigate the performance of technical trading rules in the context of portfolio performance.

Our results show that the addition of the two volatility filters and the introduction of a model switch strategy add value to the models performance in terms of annualised return, information ratio and maximum drawdown. Significant improvement has been found at both the single asset and portfolio levels. Although our results for the optimal trading frequencies differ for different assets, similar results have been achieved between the two stock indexes S&P500 and STOXX50 and between FX currency rates. In the case of stock indexes, the optimal trading frequency is about 2-4 trades per year, while for the FX currency rates, it is about 10-20 trades per year.

The rest of the chapter is organized as follows: section 2.2 presents a brief review of the relevant literature, section 2.3 describes data used and section 2.4 explains the methodology employed in this study. Section 2.5 presents the empirical results, focusing on the models performance during different periods, followed by concluding remarks in section 2.6.

2.2 Literature Review

2.2.1 Holding Period and Data Frequency

An investor's anticipated trading frequency, or investment period, is often seen as the most important single factor affecting the asset allocation decision for financial asset holdings (Douglas Van Eaton and Conover, 2002). Although the importance of the holding period is commonly recognized, it is surprising to find that most articles arbitrarily set the investment horizon to one specific time period, and so far there is no literature attempting to find the optimal trading frequency for a financial asset or a portfolio.

While the data sampling frequency is a fundamental aspect of empirical finance, there is no consensus on the selection of the data frequency relative to the expected holding period. Statistically, most econometric and time series models require more than 2000 observations for estimation purposes, which suggests using sample data of at least daily frequency. Andersen *et al.* (1999) show that using high-frequency intraday data may produce a quite significant improvement in terms of the volatility forecast errors. However, Mian and Adam (2001), among others, argue that the appropriate sampling frequency depends on the particular context: if long-term forecasts are needed, an appropriate model would be one estimated with low frequency data. In the case of using high frequency forecasts to make long-term decisions, Leung *et al.* (2000) use a cut-off point trading strategy to screen off the number of forecasts. Terui and van Dijk (2002) examine the use of time-varying weights in combining forecasts from alternative models. Roche and Rockinger (2003) use trading rules of exponential moving average (EMA) trading models with volatility filters.

2.2.2 Technical Trading and Filter Rules

Technical trading rules have been used in financial markets almost since the beginning of the markets. Nowadays it is still one of the most popular forecasting techniques in financial markets and many of the market commentaries published by financial firms and media are based on technical analysis. Apart from its popularity among market practitioners, technical trading receives less academic support and the results from academic literature about the profitability of technical trading rules are conflicting. Much of the earlier work[1] concludes that it is not possible to outperform the market with technical trading rules. Recent empirical studies show evidence of profitability from using technical trading rules. Brock *et al.* (1992) provide

[1] See, for instance, Alexander (1961) and Fama and Blume (1966).

strong support for technical strategies, where returns from their technical trading strategies outperform four popular null models: the random walk, the AR(1), the GARCH-M and the EGARCH. Blume *et al.* (1994) show that the sequence of data for both past prices and trading volume improve the predictability of equity returns within the "noisy rational expectation" framework. Kwon and Kish (2002) indicate that technical trading rules add value to capture profit opportunities over a buy-and-hold strategy, while the results are weaker in the last sub-period they consider. Sullivan *et al.* (1999) show however that the results of Brock *et al.* (1992) are substantially weakened when the survivorship bias is corrected. Ready (2002) argues that the apparent success of the Brock *et al.* (1992) moving average rules is a spurious result of datasnooping, which occurs when a given set of data is used more than once for purposes of inference or model selection. Chiarella *et al.* (1992) set out to analyze the impact of long run MA rules on the market dynamics and find that within a market maker scenario, an increase of the window length of the MA rule can destabilize an otherwise stable system.

It is well known that trend-following systems tend to perform poorly when markets become volatile. Different filters have been proposed to tackle this problem, attempting to improve the overall performance of trend-following systems. Roche and Rockinger (2003) explain that most of the time, high volatility periods correlate with periods when prices change direction, so they use a volatility filter, which reverses the signals from the original EMA system when the market volatility is high. Dunis and Chen (2005) argue that moving average convergence and divergence (MACD) models perform poorly in volatile markets, precisely because volatile markets imply frequent direction changes, and thus introduce a volatility filter, which stops trading at times of high volatility.

2.3 Data

We apply technical trading rules in the stock, bond, commodity and FX markets to test for their respective optimal trading frequencies. The FX data bank covers 9 spot FX currency rates from 02/01/1995 to 30/03/2004. The 9 currency rates are EUR/USD, USD/JPY, GBP/USD, USD/CHF, USD/CAD, AUD/USD, EUR/GBP, EUR/JPY and EUR/CHF, those rates that are most heavily traded in the foreign exchange market (BIS 2004)[2]. We use the futures data for the other three markets covering the period from 02/01/1998 to 30/03/2004. The exact time series are S&P500 (CME) and Euro STOXX50 (EUREX)[3] for the stock markets, 30-year T-Bond (CBT) and 10-year Bund (EUREX)[4] for the bond market, and Copper (LME), Aluminium (LME) and Brent Oil (IPE) for the commodity markets. The financial datasets used are daily data obtained from Datastream, the spot rates for the 9 exchange rates considered and the continuous futures contracts for the other markets.

The daily asset returns r in time period t are calculated as the percentage

[2] Since the 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. The synthetic EUR/GBP, EUR/JPY and EUR/CHF are created following the same approach.

[3] The EURO STOXX50 traded on EUREX is only available from 22/06/1998, so we use the cash market rate return from 02/01/1998 to 22/06/1998 as our futures return and generate an artificial STOXX50 futures series in that period.

[4] The Bund futures traded on EUREX available in Datastream starts on 05/10/1998, so we use the Bund future price on LIFFE from 02/01/1998 to 02/10/1998 to retrapolate the EUREX series.

change of the daily closing value p:

$$r_{t+1} = (\frac{p_t - p_{t-1}}{p_{t-1}}) \tag{2.1}$$

2.4 Technical Trading Rules: the Methodology

2.4.1 MACD

Technical trading rules have long been applied in financial markets, and the fact that technical trading rules are still one of the most popular techniques applied by market practitioners is deemed significant. The basic assumption of a technical trending system is that "everything is in the rate and the market moves in trend". Then the major task of such a trend-following system is to define the prevailing trend and identify early reversals.

One of the most widely used technical trending systems is investigated in this chapter: the moving average convergence and divergence system (MACD). An MACD system consists of two moving averages (MA), a short-term MA and a long-term MA, of the underlying asset. We use "s D - l D" to refer to a specific MACD, where s and l are the number of days in the short-term and long-term MA respectively. In such a system, the long-term MA is to identify the prevailing trend, and the short-term is the market timing device. The trading strategy based on an MACD system is to go long (or short) when the short-term MA is above (or below) the long-term MA[5]. The idea behind MA is

[5] In this thesis, once a signal is received, a trade is initiated. That position is kept until a

to smooth out a volatile time series and there are different ways to compute MA. We use the simple MA where all past observations in the MA are assigned with equal weights as[6]:

$$MA_{(t)} = (1/n)\sum_{i=1}^{n} p_{t-i} \tag{2.2}$$

2.4.2 Trend-Following Technique and Market Volatility

It is well known that trend-following systems tend to perform poorly when markets become volatile. To study how volatility affects model performance, we first need an accurate measure of market volatility. While there are numerous models proposed in the literature to measure and forecast financial market volatility, the two most popular ones are the simple variance or standard deviation and Bollerslev (1986) GARCH (1,1) model. Since we are interested in the changes in market volatility, the time varying GARCH (1,1) model is more appropriate. For the sake of simplicity, we use RiskMetrics volatility model, which can be viewed as a special case of GARCH model. RiskMetrics was developed by JP Morgan (1994) for the measurement, management and control of market risks in its trading, arbitrage and own investment account activities. The RiskMetrics volatility is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \tag{2.3}$$

---

contrary signal is produced, in which case the existing position is closed and a new opposite position is taken.

[6] In this chapter, all MAs are calculated using price level of the underlying assets, except for Brent Oil futures where the natural logarithm of the price level is used.

where σ^2 is the volatility forecast of a specific asset, r^2 is the squared return of that asset, and $\mu = 0.94$ for daily data as computed in JP Morgan (1994)[7].

We then study the relationship between the performance of different MACDs and periods of different market volatility. Five MACD models have been applied to the two time series of EUR/USD and S&P500 futures from 17/12/1998 to 30/03/2004. For simplicity, all the short-term MAs in the five MACDs are the prices level itself and the long-term MAs span from as short as 30 day to as long as 250 day[8]. The whole period is split into 6 sub-periods, ranging from periods with extremely low volatility to periods experiencing extremely high volatility[9]. The performance of the five MACDs, in terms of average daily returns, in different periods of market volatility can be found in table 2.1 for the EUR/USD and in table 2.2 for the S&P500 futures.

For the EUR/USD series, the MACDs perform poorly in all cases when the market volatility is high compared to their performance when the market is less volatile. What is more, all MACDs produce negative returns in different periods of high market volatility. This is even more obvious for the S&P500

[7] The assumption is that the mean of asset return r is zero so that $r^2_{(t)}$ represents the latest variance. In addition, at the beginning to initiate the computation, we set $\sigma^2_{(0)} = r^2_{(0)}$

[8] 32, 61 and 117 day MAs have been proved successful in currency markets, so we use these three MAs instead of 30, 50 and 100 day MAs for the EUR/USD rate (see Lequeux and Acar, 1998).

[9] Periods with different volatility levels are classified in the following way: we first calculate the rolling historical average volatility and its "volatility" (measured in terms of standard deviation σ), those periods with volatility forecasts between the average volatility (Avg. Vol.) and average plus one σ of the volatility (Avg. Vol + 1 σ) are classified as "Lower High Vol. Periods". Similarly, Medium High Vol. (between Avg. Vol. + 1σ and Avg. Vol. + 2σ) and Extremely High Vol. (above Avg. Vol. + 2σ) periods can be defined. Periods with low volatility are also defined following the same 1σ and 2σ approach, but with a minus sign. The average volatility and its "volatility" used to classify different volatility regimes in table 2.1 and 2.2 are calculated over the entire sample period. Appendix 2.1 shows the average volatility and its "volatility" computed over different sample periods. It can be seen that except for the falls in volatility in the two stock markets over the last half-year period, the numbers calculated over the entire sample period can be a good approximation for these variations.

futures market, where all MACDs generate large negative returns when the market is extremely volatile. This suggests that MACD trading rules behave differently in highly volatile markets and therefore a different strategy should be adopted when the volatility regime changes. It is also found that no single MACD performs best in all periods, and in general MACD systems with crossover between the price level and short-term MAs perform better when the market volatility is low and MACDs containing long-term MAs tend to outperform when the market is more volatile. All these findings help us to adjust our trading strategy, namely with the addition of volatility filters and the introduction of a model switch strategy, with an attempt to improve overall model performance.

Table 2.1 The average daily returns of MACDs in EUR/USD market

* 6-year period 17/12/1998 to 30/03/2004

	Extremely Low Vol.	Medium Low Vol.	Lower Low Vol.	Lower High Vol.	Medium High Vol.	Extremely High Vol.
# of Days	7	215	482	434	193	35
1D - 32 D	0.35%	0.03%	0.03%	0.01%	0.01%	-0.04%
1D - 61 D	0.35%	0.06%	0.05%	0.01%	0.01%	-0.04%
1D - 117 D	0.35%	0.05%	0.04%	-0.03%	-0.03%	0.02%
1D - 150 D	0.20%	0.06%	0.05%	-0.02%	-0.03%	0.00%
1D - 250 D	0.20%	0.05%	0.04%	0.01%	-0.01%	-0.08%

Table 2.2 The average daily returns of MACDs in S&P500 futures market

* 6-year period 17/12/1998 to 30/03/2004

	Extremely Low Vol.	Medium Low Vol.	Lower Low Vol.	Lower High Vol.	Medium High Vol.	Extremely High Vol.
# of Days	13	161	577	456	130	42
1D - 30 D	0.42%	0.04%	0.00%	0.04%	-0.09%	-0.53%
1D - 50 D	0.05%	0.03%	0.01%	0.03%	-0.15%	-0.75%
1D - 100 D	0.05%	-0.02%	0.02%	-0.08%	-0.10%	-0.62%
1D - 150 D	0.05%	0.02%	0.04%	-0.03%	0.00%	-0.62%
1D - 250 D	0.05%	0.01%	0.12%	0.01%	0.01%	-0.62%

2.4.3 Volatility Filter Rules

In this chapter, we use the symbol $MA^{(p)}{}_{(t+1,t)}$ to denote the trading signals from an MACD model at time *t* for time *t+1*, where *p* is the volatility filter imposed on that model: *p* takes the value of 0 if there is no volatility filter, it takes the value of 1 when a "no-trade" filter is used and 2 when a "reverse" filter is in use.

2.4.3.1 "No-trade" Strategy

Since MACD models are found to perform poorly in volatile markets, following Dunis and Chen (2005) the first filter rule is simply to stop trading when the market volatility is forecast to be higher than a certain threshold T[10]. The

[10] In table 2.1 and 2.2, we have shown that MACD models perform poorly in volatile markets globally over the entire sample periods, for simplicity, the threshold of the volatility filters T is therefore set at the cutoff points that split the sample period into high and low volatility regimes as explained in footnote 9.

previous MACD trading rules are thus combined with the following "no-trade" strategy:

$$MA^{(1)}{}_{(t+1,t)} = \begin{cases} MA^{(0)}{}_{(t+1,t)} & \sigma^2{}_{(t+1,t)} < T \\ 0 & \sigma^2{}_{(t+1,t)} > T \end{cases}$$

2.4.3.2 *"Reverse" Strategy*

When a market experiences high volatility, MACD models produce negative returns most of the time. Roche and Rockinger (2003), who explain that high volatility periods often correlate with periods when prices change direction, propose the following filter, which is to reverse the signals generated when the market volatility is forecast to be higher than the chosen threshold. We use this strategy as the second filter to our MACD trading rules:

$$MA^{(2)}{}_{(t+1,t)} = \begin{cases} MA^{(0)}{}_{(t+1,t)} & \sigma^2{}_{(t+1,t)} < T \\ -\left(MA^{(0)}{}_{(t+1,t)} \right) & \sigma^2{}_{(t+1,t)} > T \end{cases}$$

2.4.3.3 *Model Switch Strategy*

We find previously that it seems impossible to identify an MACD model as the "best" over all sub-periods, and not surprisingly, different MACDs perform best in periods of different market volatility. In general, MACD systems with crossover between the price level and short-term MAs perform better when the market is in a low volatility regime and MACD containing long-term MAs tend to outperform when the market is more volatile. It seems that certain MACD only perform well in a certain volatility regime, and their performance deteriorates when market volatility changes significantly. This leads us to introduce a new "combined trading rule", which we call the model switch strategy. The strategy is to take the signals from one MACD when the volatility forecasts are higher than a threshold T' and to take the signals from another MACD when the forecasts are lower than the threshold T'. Since the threshold T' for the model switch strategy is chosen to be always lower than the previously determined threshold T, the trading signals from a model switch strategy with a "reverse" filter can be expressed as:

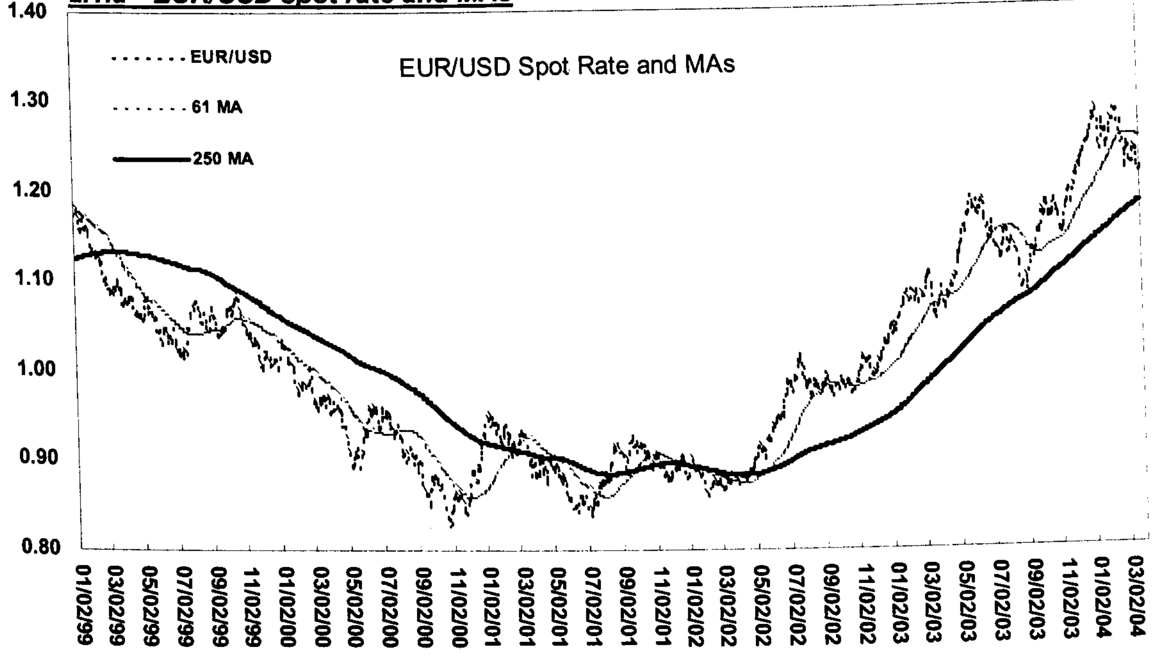
$$Switch^{(2)}_{(t+1,t)} = \begin{cases} MA1^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T' \\ MA2^{(0)}_{(t+1,t)} & T' < \sigma^2_{(t+1,t)} < T \\ -(MA2^{(0)}_{(t+1,t)}) & \sigma^2_{(t+1,t)} > T \end{cases}$$

2.4.4 Filter Rules: An Illustration

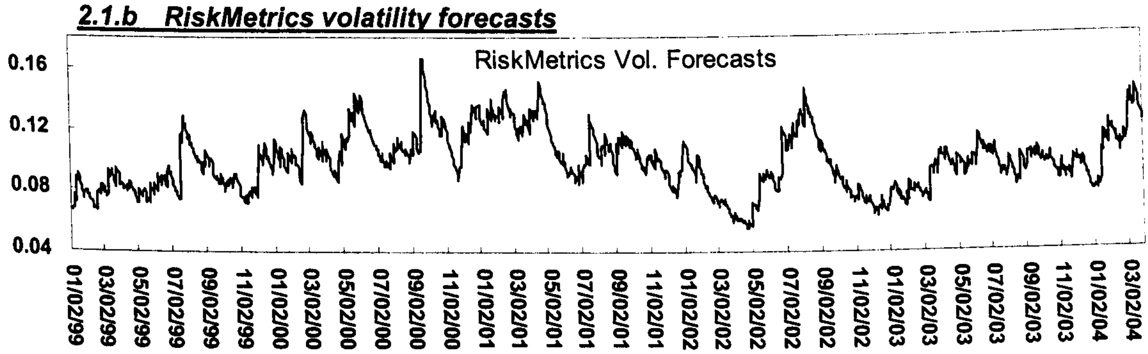
Figure 2.1 gives a simple illustration on how the model switch strategy works in the EUR/USD market. Figure 2.1.a graphs the spot rate and the two MAs (61D and 250D) of the series. The market experiences an obvious downward trend in the period from 17/12/1998 to 25/10/2000, and it then reverses to an upward trend until the end of the sample period. Both the 61D and 250D MAs are able to identify this trend and the two MACDs based on the crossover between the spot rate and MAs generate satisfactory results in terms of cumulative returns as shown in figure 2.1.c. The 1D-61D MACD outperforms

Figure 2.1 An illustration of how the model switch strategy works in EUR/USD spot market

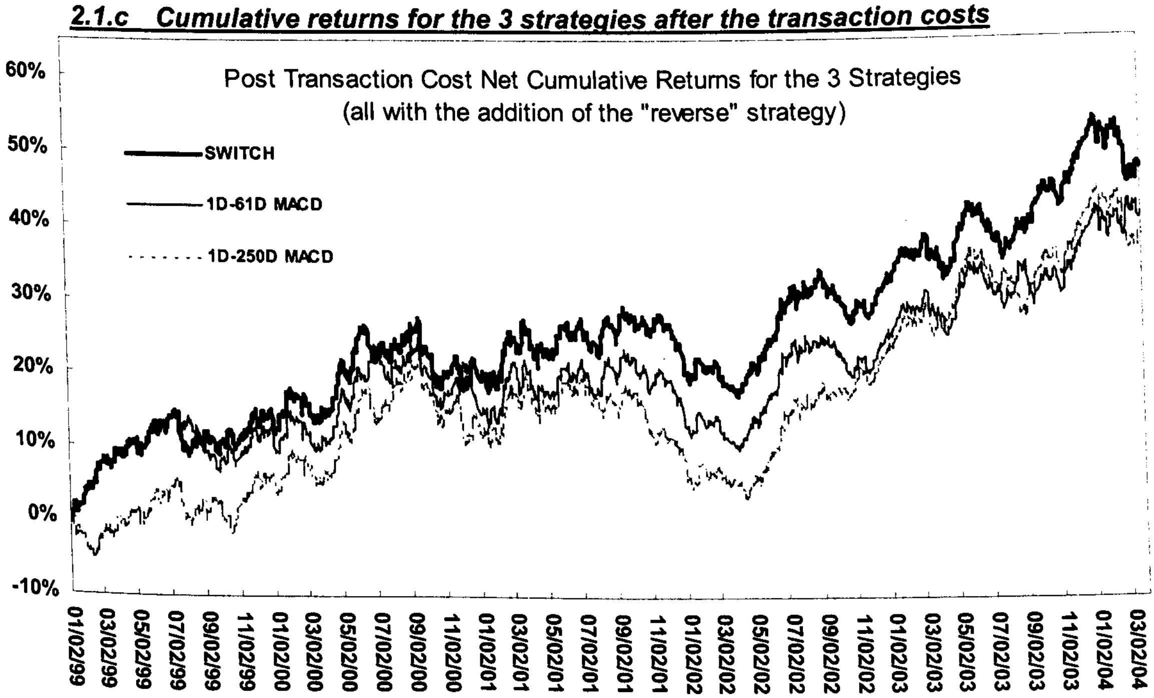
2.1.a EUR/USD spot rate and MAs



2.1.b RiskMetrics volatility forecasts



2.1.c Cumulative returns for the 3 strategies after the transaction costs



the 1D-250D MACD in that the former is able to catch the reversal more quickly and thus able to better profit from short-term market movements. For instance, during the long-term upward trend from 27/05/2003 to 03/09/2003, there is a short-term reversal. While the 1D-250D MACD still give a long position signal, the 1D-61D MACD is able to signal a short position on 07/07/2003, and close that position on 12/09/2003 with a profit of 0.29%. But the short-term MACD has the problem of over-reacting by giving "whipsaw" signals: taking another example, 1D-61D MACD takes a short position on 17/03/2003 and closes it on 28/03/2003 with a loss of 0.59% and extra transaction costs. Our remedy to this problem is to use the market volatility forecasts as an indicator to pick the right signals. Depending on the volatility forecasts, the positions taken are "switched" between the signals from the two MACDs. With such a switch strategy, the overall cumulative return is increased to 2.93% for the first example and makes no loss in the second example. Overall the switch model is able to consistently outperform both MACDs in the entire sample period shown in figure 2.1.c[11].

2.5 Empirical Results

We assess the performance of technical rules at both the single asset and portfolio level. The first portfolio formed is an FX portfolio consisting of the 9 FX currency rates that are most heavily traded in the market, and the weights

[11] To make model performance comparable, the cumulative performances shown in figure 2.1.c are the performances of the 3 trading strategies, i.e. the 1D-61D, 1D-250D and the model switch strategy, with the addition of the "reverse" volatility filter.

are allocated based on their trading volume in the FX market. We obtain the market trading volume from the recent BIS triennal report 2004 (BIS 2004)[12] (they represent over 78% of the USD 1.8 trillion daily FX turnover reported for April 2004), and weights are shown in table 2.3[13]. The entire data period is split into 4 periods to see if the models performance is consistent over different periods. The FX portfolio performance is shown in table 2.6 and 2.7. In the long run currency returns can be seen as zero, and therefore a traditional passive benchmark, for example the buy-and-hold strategy is not appropriate. Lequeux and Acar (1998) introduce a dynamic currency index (AFX index) using 3 simple MACD (namely 1D-32D, 1D-61D and 1D-117D) strategies with each MACD taking the same weight in generating trading signals. They find that the AFX index has high correlation with and low tracking error to currency traders' performance. Following the same 1D-32D, 1D-61D and 1D-117D MACD combination strategy, we form a dynamic FX benchmark portfolio using the 9 FX currency rates mentioned above. It should be noted that for simplicity in this chapter all FX currency returns are exclusive of interest income or payments for holding a specific currency: these could further enhance the models performance displayed throughout, but as our objective in this chapter is to compare the relative performance of MACD models with and without volatility filters, the exclusion of interest income or payments can be ignored.

---

[12] We use the notation of the International Organisation for Standardisation (IOS) for all the exchange rates considered.

[13] The asset allocations set for all the portfolios in this chapter remain unchanged for the entire data sample period. For example, for EUR/USD series in table 2.3, the trading simulation assumes that 35.76% of the total investment is used to either long or short the EUR/USD rates. The same remark also applies to portfolio 2 and 3 formed in the chapter.

Table 2.3 Portfolio 1 (FX portfolio) currency allocation

Currency	EUR /USD	USD /JPY	GBP /USD	USD /CHF	USD /CAD	AUD /USD	EUR /GBP	EUR /JPY	EUR /CHF
Weights	35.76%	21.13%	17.49%	5.57%	5.07%	6.42%	3.07%	3.64%	1.85%

Two more portfolios are formed. Both portfolios consist of 5 assets, with each asset taking equal weight in the portfolio. The assets are so selected that each portfolio has at least one stock, one bond, one exchange rate and one commodity. Except for FX rates which are spot rates, all assets are exchange-traded futures contracts[14]. Like the FX portfolio, the entire sample period for these two portfolios is split into 4 periods to measure the consistence of the trading performance over different periods of time. Model performance for portfolio 2 and 3 is shown in table 2.8 and table 2.9[15].

Table 2.4 Portfolio 2 asset allocation

Assets	S&P500	EUR/USD	COPPER	BRENT OIL	BUND
Weights	20%	20%	20%	20%	20%

Table 2.5 Portfolio 3 asset allocation

Assets	USD/JPY	GBP/USD	ALUMINIUM	STOXX50	T-BOND
Weights	20%	20%	20%	20%	20%

[14] This is done to replicate the situation of small or medium-size investors who can ill afford to trade cost efficiently the cash stock, bond and commodity markets.

[15] In table 2.8 and 2.9, the "Combined MACD" strategy is to take the best combinations of MACDs in different markets. The "Optimal" strategy is to select the best models in different markets. More specifically, for portfolio 2, the "Optimal" strategy adopts the model switch strategy in SP500, EUR/USD and Bund markets, and takes "Combined MACD" Strategy in the Copper and Brent Oil markets. For portfolio 3, the "Optimal" strategy takes the model switch strategy in USD/JPY, Aluminum and T-bond markets, and the "Combined MACD" in the other two markets.

The level of transaction costs is important to the trading frequency. Usually the higher the transaction costs, the less frequently an asset should be traded. In this study, for the FX currency portfolio, we follow Lequeux and Acar (1998) and set the transaction cost as 0.03% per round-trip transaction for all currency rates in this portfolio. While for portfolio 2 and 3, to reflect the real world fund management, transaction costs are set as 0.01% for EUR/USD and GBP/USD, 0.02% for USD/JPY, 0.06% for Bund and T-Bond, and 0.12% for all other futures contracts.

In addition to the single MACDs, we also combine 2 or 3 MACDs to form a "combined MACD", with each MACD taking equal weight (see, for instance, table 2.7)[16]. For each asset traded, a benchmark is formed. The benchmarks for all bonds, stock indexes and commodity futures are passive buy-and-hold strategies, and the benchmark for currency rates is the joint performance of the 1D-32D, 1D-61D and 1D-117D MACDs as suggested by the AFX index. For the portfolio, the benchmark is the combined performance of these individual benchmarks.

The performance of different trading rules is assessed in terms of post-transaction-cost annualised return, post-transaction-cost information ratio and maximum drawdown. Performance statistics for the 3 portfolios can be found in the 4 tables from table 2.6 to table 2.9, with their cumulative performance in figure A.1 in appendix. Performance statistics for all single

[16] With a "combined MACD" strategy, the final trading signal equals the sum of the signals generated by each individual MACD strategy. For example with a trading strategy consisting of two MACDs, if one MACD gives a signal to go long and the other to go short, the final trading strategy will be stay out of the market until both signals agree. This combination rule applies to all the "combined MACD" strategy in the thesis.

assets can also be found in table A.6 to A.15 in appendix.

2.5.1 Results for Portfolio 1 (FX portfolio)

The addition of either the "no-trade" or the "reverse" filter seems to work well for the currency markets. In most cases, the "reverse" strategy performs better than the "no-trade" strategy in terms of annualised return and information ratio. However, the "no-trade" strategy has the lowest maximum drawdown. This result is obvious as the "no-trade" strategy takes the more prudent altitude to withdraw from market exposure when the volatility is expected to be high rather than the aggressive "reverse" strategy, which takes the opposite position from the prevailing one. Also with a "no-trade" strategy, investors are able to free funds out of the high volatility market and invest them in other markets for short-term profits. So there is no overwhelming outperformance of one filter over the other, and it is up to investors to choose the right strategy based on their risk tolerance in volatile markets. But it is obvious that the market behaves differently at high volatility levels and prompt action should be taken taking account of the volatility change.

In the longer-term (i.e. the overall performance for the 5 and 10-year periods), it looks that the 1D-61D works the best among all single MACDs. But since trades rarely rely on one single MA, we also measure the performance for the combination of several MAs and find that 1D-61D and 1D-250D are the best overall in combined MACDs, they outperform other combinations of MACDs, including the 1D-32D/1D-61D/1D-117D combination used by the AFX in

Table 2.6 Performance statistics for FX portfolio (with single MACD)

	10-year Period (18/12/1995 - 30/03/2004)				*5-year Period (04/01/1999 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1D- 5D	63	1.70%	0.31	-6.23%	61	2.83%	0.49	-6.23%	59	4.22%	0.75	-4.76%	55	5.12%	0.78	-3.29%
1D- 32D	23	2.05%	0.35	-8.59%	23	1.66%	0.28	-8.59%	22	7.67%	1.32	-3.49%	20	6.41%	0.96	-4.68%
1D- 61D	14	3.79%	0.64	-7.63%	14	3.71%	0.60	-7.63%	13	8.87%	1.47	-5.22%	9	9.84%	1.38	-3.81%
1D- 117 D	12	0.91%	0.15	-12.95%	13	0.06%	0.01	-12.95%	13	6.70%	1.12	-5.71%	13	3.30%	0.46	-6.43%
1D- 250 D	6	4.16%	0.70	-9.99%	6	4.11%	0.66	-9.99%	4	11.92%	1.82	-6.15%	4	15.15%	1.97	-4.80%
Strategy #2	*MACD with No-trade volatility filter*															
1D- 5D	54	2.89%	0.64	-6.27%	53	3.49%	0.73	-6.27%	57	3.68%	0.67	-4.46%	45	13.13%	2.38	-1.92%
1D- 32D	21	3.07%	0.65	-6.90%	22	3.01%	0.59	-6.20%	22	7.24%	1.28	-3.58%	19	7.11%	1.25	-4.45%
1D- 61D	15	4.22%	0.88	-5.84%	16	5.06%	0.98	-5.84%	15	9.06%	1.56	-4.47%	11	10.59%	1.79	-2.94%
1D- 117 D	13	1.54%	0.32	-11.09%	13	1.53%	0.29	-11.09%	14	6.55%	1.13	-5.39%	10	5.64%	0.95	-4.60%
1D- 250 D	9	4.51%	0.93	-8.20%	9	4.75%	0.90	-8.20%	6	11.52%	1.82	-5.57%	8	12.85%	2.11	-4.53%
Strategy #3	*MACD with Reverse volatility filter*															
1D- 5D	66	3.37%	0.67	-6.96%	65	3.49%	0.67	-6.96%	60	2.95%	0.54	-4.47%	60	20.33%	3.41	-1.93%
1D- 32D	29	3.80%	0.73	-9.11%	29	4.07%	0.75	-4.82%	25	6.74%	1.20	-3.81%	25	7.59%	1.20	-4.82%
1D- 61D	21	4.52%	0.86	-8.00%	22	6.26%	1.14	-4.69%	18	9.20%	1.61	-3.80%	17	11.16%	1.81	-3.18%
1D- 117 D	19	2.04%	0.39	-11.70%	19	2.81%	0.51	-11.70%	17	6.36%	1.11	-5.07%	20	7.58%	1.27	-4.65%
1D- 250 D	14	4.80%	0.90	-7.99%	15	5.32%	0.95	-7.99%	10	11.10%	1.78	-5.33%	13	10.51%	1.69	-6.16%
FX Benchmark	**16**	**2.25%**	**0.43**	**-8.88%**	**16**	**1.81%**	**0.33**	**-8.88%**	**16**	**7.75%**	**1.44**	**-4.33%**	**14**	**6.52%**	**1.06**	**-4.54%**

Table 2.7 Performance statistics for FX portfolio (with combined MACD)

	10-year Period (18/12/1995 - 30/03/2004)				*5-year Period (04/01/1999 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-15 D / 1-25 D / 1-61 D	24	2.89%	0.57	-7.48%	24	2.69%	0.51	-7.48%	22	8.10%	1.58	-3.88%	20	8.58%	1.47	-3.74%
1-32 D / 1-61 D / 1-117D	16	2.25%	0.43	-8.88%	16	1.81%	0.33	-8.88%	16	7.75%	1.44	-4.33%	14	6.52%	1.06	-4.54%
1-32 D / 1-61D	18	2.92%	0.54	-7.85%	18	2.69%	0.47	-7.85%	18	8.27%	1.47	-3.88%	15	8.12%	1.24	-4.01%
1-61 D / 1-250 D	10	3.98%	0.76	-7.01%	10	3.92%	0.71	-7.01%	9	10.39%	1.87	-4.75%	6	12.53%	1.98	-3.32%
Strategy #2	*MACD with No-trade volatility filter*															
1-15 D / 1-25 D / 1-61 D	22	3.81%	0.91	-4.31%	23	4.03%	0.89	-4.06%	23	8.38%	1.67	-3.64%	17	12.81%	2.63	-2.55%
1-32 D / 1-61 D / 1-117D	16	2.97%	0.69	-5.62%	16	3.23%	0.69	-5.62%	17	7.64%	1.46	-4.10%	13	7.81%	1.45	-3.33%
1-32 D / 1-61D	18	3.66%	0.81	-5.00%	18	4.05%	0.83	-5.00%	18	8.17%	1.51	-3.64%	14	8.88%	1.63	-3.16%
1-61 D / 1-250 D	11	4.40%	1.01	-6.29%	11	4.94%	1.06	-6.29%	10	10.31%	1.92	-4.30%	8	11.76%	2.09	-2.84%
Strategy #3	*MACD with Reverse volatility filter*															
1-15 D / 1-25 D / 1-61 D	29	4.45%	0.99	-6.02%	30	5.08%	1.09	-3.43%	25	8.56%	1.72	-3.43%	25	16.65%	3.09	-2.23%
1-32 D / 1-61 D / 1-117D	22	3.49%	0.76	-6.11%	22	4.42%	0.92	-5.19%	20	7.45%	1.45	-3.86%	20	8.80%	1.66	-3.72%
1-32 D / 1-61D	24	4.18%	0.87	-6.37%	25	5.19%	1.03	-3.89%	21	7.98%	1.50	-3.45%	20	9.40%	1.59	-3.89%
1-61 D / 1-250 D	15	4.72%	1.01	-6.62%	16	5.86%	1.19	-5.56%	13	10.18%	1.92	-3.86%	13	10.90%	2.06	-3.40%
FX Benchmark	**16**	**2.25%**	**0.43**	**-8.88%**	**16**	**1.81%**	**0.33**	**-8.88%**	**16**	**7.75%**	**1.44**	**-4.33%**	**14**	**6.52%**	**1.06**	**-4.54%**

Table 2.8 Performance statistics for portfolio 2

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-32 D / 1-61 D / 1-117D	78	1.75%	0.21	-16.37%	72	3.38%	0.40	-9.20%	68	7.07%	0.84	-4.66%	63	18.22%	2.19	-3.67%
Combined MACD	65	8.50%	0.94	-11.88%	64	9.35%	1.06	-11.88%	63	15.05%	1.77	-5.56%	53	30.38%	3.76	-3.27%
Model Switch	77	8.14%	0.83	-14.75%	77	9.16%	0.97	-14.75%	75	16.32%	1.83	-6.53%	69	33.12%	3.72	-3.67%
Optimal	73	8.89%	0.96	-11.79%	71	9.16%	1.03	-11.79%	75	15.29%	1.75	-6.28%	55	30.59%	3.69	-3.53%
Strategy #2	*MACD with No-trade volatility filter*															
1-32 D / 1-61 D / 1-117D	76	4.93%	0.65	-9.70%	68	5.52%	0.75	-8.01%	58	18.47%	2.39	-3.67%	12	19.20%	2.49	-3.67%
Combined MACD	63	12.32%	1.55	-8.17%	60	14.15%	1.85	-4.58%	59	29.54%	3.87	-3.08%	13	29.83%	3.93	-3.26%
Model Switch	77	12.24%	1.44	-7.97%	76	14.62%	1.78	-4.98%	77	31.84%	3.80	-2.91%	15	32.94%	3.93	-2.91%
Optimal	72	13.04%	1.61	-7.62%	68	14.19%	1.83	-4.41%	63	29.32%	3.77	-3.58%	13	30.15%	3.88	-3.58%
Strategy #3	*MACD with Reverse volatility filter*															
1-32 D / 1-61 D / 1-117D	97	7.81%	0.95	-8.98%	85	7.39%	0.91	-8.23%	73	18.60%	2.36	-3.67%	15	19.41%	2.46	-3.67%
Combined MACD	86	15.65%	1.78	-6.51%	79	18.52%	2.19	-4.85%	67	28.68%	3.63	-3.83%	16	29.56%	3.76	-3.83%
Model Switch	102	15.88%	1.71	-6.19%	97	19.69%	2.18	-5.31%	87	30.56%	3.57	-3.23%	17	31.72%	3.70	-3.23%
Optimal	97	16.69%	1.88	-6.12%	90	18.77%	2.20	-4.64%	73	28.04%	3.50	-3.96%	15	28.93%	3.61	-3.96%
Benchmark	**15**	**9.86%**	**1.06**	**-22.16%**	**17**	**6.64%**	**0.72**	**-17.70%**	**22**	**33.97%**	**3.81**	**-2.42%**	**4**	**33.97%**	**3.81**	**-2.42%**

Table 2.9 Performance statistics for portfolio 3

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-32 D / 1-61 D / 1-117D	86	-2.52%	-0.36	-19.36%	88	-3.03%	-0.39	-16.73%	96	-5.60%	-0.59	-9.35%	103	-4.55%	-0.66	-8.84%
Combined MACD	33	4.64%	0.61	-10.76%	36	3.48%	0.41	-10.76%	36	7.04%	0.69	-6.10%	39	3.54%	0.46	-10.76%
Model Switch	28	5.82%	0.74	-11.26%	30	5.65%	0.65	-11.26%	35	7.47%	0.71	-6.13%	38	6.28%	0.78	-9.33%
Optimal	26	5.81%	0.74	-11.21%	28	5.23%	0.61	-11.21%	33	7.43%	0.71	-5.82%	32	6.42%	0.82	-9.09%
Strategy #2	*MACD with No-trade volatility filter*															
1-32 D / 1-61 D / 1-117D	83	0.22%	0.04	-9.54%	84	0.48%	0.08	-9.54%	97	-0.31%	-0.05	-5.61%	72	5.69%	1.27	-3.10%
Combined MACD	37	7.10%	1.14	-6.49%	39	6.88%	1.08	-6.49%	44	8.13%	1.26	-6.23%	37	19.86%	4.11	-2.96%
Model Switch	37	7.76%	1.22	-6.79%	38	8.66%	1.33	-6.41%	43	10.66%	1.59	-6.41%	33	23.19%	4.80	-2.38%
Optimal	34	7.88%	1.25	-6.42%	35	8.42%	1.31	-6.25%	37	10.80%	1.64	-5.45%	33	23.19%	4.80	-2.38%
Strategy #3	*MACD with Reverse volatility filter*															
1-32 D / 1-61 D / 1-117D	100	2.61%	0.40	-8.19%	101	3.56%	0.51	-8.19%	107	3.66%	0.54	-4.32%	94	8.59%	1.96	-2.24%
Combined MACD	53	9.36%	1.35	-6.25%	55	10.06%	1.39	-6.25%	51	12.70%	1.87	-6.25%	59	20.59%	4.41	-2.10%
Model Switch	52	9.56%	1.35	-6.41%	52	11.54%	1.58	-6.41%	50	15.02%	2.18	-6.41%	51	22.82%	4.82	-2.14%
Optimal	49	9.80%	1.39	-5.99%	50	11.46%	1.57	-5.78%	44	15.16%	2.21	-5.48%	55	23.92%	5.09	-1.49%
Benchmark	**35**	**2.12%**	**0.32**	**-17.48%**	**35**	**-0.47%**	**-0.07**	**-16.23%**	**44**	**7.55%**	**1.19**	**-5.30%**	**26**	**16.81%**	**3.25**	**-4.05%**

terms of return, information ratio with an acceptable level of maximum drawdown. Although the performance of this combination is not always the best in different sub-periods, it produces the most consistent results over the sample periods. So we retain the 1D-61D and 1D-250D as our best model for the FX currency portfolio.

We then look at the more recent performance: 2003 and the recent half-year. Although several other single MACDs produce great results with some information ratios above 2 in the recent half-year period, the 1D-61D and 1D-250D combination keeps performing the best among all combined strategies. The reason for the stunning performance for some single MACDs could be either the result of datasnooping that are documented in previous studies on technical trading rules or the result of USD depreciation against all major currencies since early 2002 as the USD is the most heavily traded currency, with 91.44% of the FX portfolio currencies being "dollar related". An MA that is able to capture this depreciation in one currency rate works well in other currency rates as well.

As far as trading frequency is concerned, the addition of the "reverse" filter increases the number of trades compared to the original MACD strategy with no filters as expected. The "no-trade" strategy generally decreases the trades by exiting the market at high volatility levels. But if the number of trades from a simple MACD is already low, this strategy will inversely increase the number of trades. Overall, although the trading performance very much depends on the models and strategies employed, with the study of MACD, the optimal is around 11 trades per year for a passive "no-trade" strategy and around 16 trades per year for a more aggressive "reverse" strategy. This suggests that even for an active currency trader, a trading frequency of about 1 or 2 times per month seems optimal. It implies that an investor should establish a currency position with an expectation, on average, to hold this position at least half a month before closing it out. Practically, this information is meaningful when building a trading system: for example, a 10-day forecast horizon or a 10 or 15 day time delay filter can be added[17].

In this study, we follow Lequeux and Acar (1998) and set the transaction cost as 0.03% per round-trip transaction for all currency rates in the FX portfolio. However, there has been a fall in transaction costs in recent years, so we measure the MACD model performance with lower transaction costs to see whether it will affect the results reached above. Different levels of transaction costs at 0.025%, 0.02%, 0.015% and 0.01% are applied[18]. We find that although lower transaction costs tend to benefit more on the performance of MACD strategy with short-term MAs than long-term MAs, the combination of the 1D-61D and 1D-250D produces the most consistent results across different periods. The optimal trading frequency for the FX currency rates obtained from this strategy is therefore unchanged. As far as the impact on volatility filters is concerned, the models with "no-trade" strategy incur less transaction costs since it generates fewer trades than the "reverse" strategy (see table A.2-A.5 in appendix). Also the "no-trade" strategy implies being out of the market at times, thus translates overall into lower transaction costs. But

---

[17] A time delay filter requires the buy or sell signal to remain valid for a pre-specified period of time before action is taken.

[18] Model Performance with transaction costs at 0.02% and 0.01% are shown in appendix, while performance with transaction costs at other level can be obtained upon request.

differences between the performances of the two filter strategies are still marginal.

2.5.2 Results for Portfolio 2 and 3

Generally speaking, similar results have been reached for portfolio 2 and 3: firstly, the addition of the two volatility filters keeps adding value to the trading performance with few exceptions, and the "reverse" strategies are able to outperform the "no-trade" strategies in most cases. Secondly, it is still hard to discriminate between the two filters. Overall the "reverse" filter performs well in terms of information ratio, but the "no-trade" filter performs better in terms of maximum drawdown. This is particularly important for stock and commodity futures markets where average market volatility is high and the maximum drawdown could be intolerably high for long periods. Thirdly, combining two simple MACDs can improve the performance from a single MACD, in terms of both the information ratio and the maximum drawdown.

Generally, technical trading rules seem to work better in stock and currency markets than they do in bond and commodity markets. This is a quite interesting finding since there is no previous paper, to the best of our knowledge, which compares the predictability of technical trading rules in different markets. Besides, the model switch strategy proposed works well, and it is interesting to find that in markets where the MACD strategy works well, the model switch model outperforms the regular MACD combination models in most cases.

Overall the technical trading rules, especially with the addition of volatility filters, have outperformed the relative passive benchmarks in all markets[19]. This is more obvious looking at portfolios, where our optimal model (named as "Optimal" in table 2.8 with the addition of a "reverse" filter) chosen for portfolio 2 can generate a 16.69% annualised post-transaction-cost return and information ratio at 1.88 with merely -6.12% maximum drawdown for a 6-year period, compared to 9.86%, 1.06 and –22.16% for the benchmark respectively[20,21]. For portfolio 3, although not as good as portfolio 2, the 9.80% annualised return and 1.39 information ratio with –5.99% maximum drawdown are way above the benchmark.

In the stock futures markets, results for both S&P500 and Euro STOXX50 suggest that the optimal trading frequency is around 2-4 times per year when applying a prudent "no-trade" strategy. In the currency markets, as suggested by the FX portfolio, the optimal trading frequency for single currency rates like EUR/USD, USD/JPY and GBP/USD remains between 10-20 trades per year depending on the filter chosen. It is not surprising to find that results are similar between stock indexes and between different currency rates, but the optimal trading frequencies vary much between different commodity futures, as the latter are very different assets. In the commodity markets, the optimal periods for Aluminium, Copper and Brent Oil are 12-18, 6-7 and 32-42 trades respectively.

---

[19] For all currency rates, the benchmark is based on an active trading rule, which combines the performance of the 1D-32D, 1D-61D and 1D-117D MACDs suggested by AFX currency index.

[20] Again the "Optimal" strategy in table 2.8 and 2.9 is to select the best models, among "combined MACD" and "Model Switch" strategies, in different markets.

[21] The benchmark for the portfolio is the combined performance of the benchmarks for each single asset in the portfolio.

As for the bond, the optimal trading frequencies are 5-8 trades per year for 30-year T-bond and 11-18 trades per year for the 10-year Bund.

Finally, the performance tables presented above show that the profitability of technical trading rules before the addition of volatility filters are inconsistent across different sample periods. This phenomenon of inconsistence was also documented in the literature[22]. This may be due to the fact that markets may trend for varying time periods in various markets (Lequeux and Acar 1998).

2.6 Concluding Remarks

Technical trading rules have been used in financial markets for decades, and are still one of the most popular forecasting techniques in financial markets. But technical trending systems are known to perform poorly in volatile markets. The primary motivation of this chapter was to investigate the performance of technical trending systems in different volatility regimes. We then proposed volatility filters to enhance the performance of these trading rules.

We applied different technical trading rules to a variety of financial assets in the stock, bond, FX and commodity markets. It is found that technical trading rules perform poorly in periods when market volatility is high, and therefore two volatility filters were proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals

[22] See, for instance, Brock *et al.* (1992) for stock markets and LeBaron (1991, 1992) for the foreign exchange market.

from a simple MACD are reversed if the market volatility is higher than a given threshold. Compared with previous papers focusing on the performances between MACDs with different window lengths, in this chapter, we also compared the impact of volatility regime changes on MACDs with different window lengths. We found that MACDs consisting of short-term MAs tend to outperform those MACDs with long-term MAs when the market is relatively stable, while the latter performs better in more volatile periods. We then proposed a model switch strategy, where signals from different MACD systems are taken depending on the prevailing market volatility.

Our results show that the two volatility filters added have significantly improved the models performance in most cases during the sample periods. The strategy with "reverse" filters performs best overall in terms of post-transaction-cost annualised return and information ratio, while the strategy with "no-trade" filters perform best in terms of maximum drawdown. The model switch strategy we proposed has performed well, especially in the stock, currency and bond markets, where it produces the best and most consistent performance in most cases. While some performance of these technical trading rules are not persuasively "good" when applied to single assets, the performances at portfolio levels are overwhelmingly good: portfolio 2 generates a 16.69% annualised post-transaction-cost return and an information ratio of 1.88 with a mere -6.12% maximum drawdown for a 6-year period, and 9.80%, 1.39 and –5.99% respectively for portfolio 3, way above the performance statistics of their respective benchmarks.

Finally, although our results for the optimal trading frequencies differ for the different assets under review, similar results have been achieved for the two stock indexes (S&P500 and STOXX50) and for the FX currency rates. In case of the stock indexes, the optimal trading frequency is about 2-4 trades per year, while for the FX rates, the optimal frequency is 10-20 trades per year. But for very different assets such as the commodities studied in this chapter, the optimal trading frequencies are understandably different.

CHAPTER 3

Volatility Filters for Asset Management:

An Application to Managed Futures

Chapter Overview

Technical trading rules are known to perform poorly in periods when volatility is high. Different from previous studies on technical trading rules which base their findings from an academic perspective, this chapter relates the findings from chapter 2 to the real world business: two portfolios, which are highly correlated with a managed futures index and a currency traders' benchmark index are formed to replicate the performance of the typical managed futures and managed currency funds. The primary motivation of this chapter is to study whether the addition of volatility filters can improve model performance of these two portfolios with the hope that the proposed techniques will then have both academic and industrial significance.

Two volatility filters are proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from a simple moving average convergence and divergence (MACD) are reversed if market volatility is higher than a given threshold.

Our results show that the addition of the two volatility filters adds value to the models performance, which confirms the findings from chapter 2.

3.1 Introduction

Financial forecasting has always been a main focus of the financial and economic literature. Many articles proposing numerous simple or more sophisticated forecasting techniques have claimed that a trading strategy based on their forecasts can outperform that of a buy-and-hold strategy or some other benchmark forecasting techniques. These trading strategies usually require the underlying assets to be traded actively, while in practice trading on a high-frequency basis in some markets is not feasible simply because of transaction costs. In markets like the stock and bond cash markets, the benefits from switching market positions at high frequency can hardly compensate for the transaction costs incurred. Transaction costs in most futures markets and foreign exchange (FX) cash markets are much lower compared to other financial markets. The low transaction costs along with the ability to "go short" easily in these markets make it possible to profit from active trading strategies. As a matter of fact, the managed futures and managed currency traders are the most active market players.

Despite the fact that technical trading rules have been extensively studied, most of these articles build their findings from an academic perspective, while few of them relate their results to the real world of investment. This chapter tries to relate our findings from the previous chapter to the real business world by forming two portfolios that are highly correlated with a managed futures index and a currency traders' benchmark index, and which replicate the performance of the typical managed futures and managed currency funds.

The major motivation for this chapter is to extend our previous findings and study whether the addition of volatility confirmation filters, based on the underlying market volatility, can help to improve the performance of the typical managed futures and managed currency funds. The proposed techniques are expected to have both the academic and industrial significance.

Of the two portfolios formed, the futures portfolio is highly correlated with the CSFB/Tremont managed futures index and is built to mimic the performance of typical managed futures funds. Following Lequeux and Acar (1998) who create a dynamic currency futures index (AFX), we also form an FX portfolio using the 9 most heavily traded FX spot rates replicating average currency managers. The specifications of the moving average convergence and divergence (MACD) used in the two dynamic portfolios are the ones applied by Lequeux and Acar (1998) who show that a combination of time spans of 32, 61 and 117 days provide the best balance between diversification and simplicity while at the same time reproducing well the performance of currency fund managers.

Two volatility filters are proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from a simple MACD are reversed if the market volatility is higher than a given threshold.

Our results show that the addition of the two volatility filters adds value to the portfolios performance in terms of annualised return, maximum drawdown and risk-adjusted information ratio in all the 3 periods considered. As for the two filters applied, the "reverse" strategy seems to outperform the "no-trade" strategy for most performance measures most of time.

The rest of the chapter is organized as follows: section 3.2 presents a brief review of the relevant literature, section 3.3 explains the methodology and section 3.4 describes the data used. Section 3.5 presents the empirical results, focusing on the models performance during different periods, followed by concluding remarks in section 3.6.

3.2 Literature Review

The results from literature about the profitability of technical trading rules are conflicting. Much of the earlier work[23] concludes that it is not possible to outperform the market using technical trading rules. However Brock *et al.* (1992) provide strong support for technical strategies, with returns from their technical trading strategies outperforming four popular null models: the random walk, the AR(1), the GARCH-M and the EGARCH. Blume *et al.* (1994) show that the sequence of data for both past prices and trading volume improve the predictability of equity returns within the "noisy rational expectation" framework. Kwon and Kish (2002) find that technical trading rules add value to capture profit opportunities over a buy-and-hold strategy. Sullivan *et al.* (1999) show however that the results of Brock *et al.* (1992) are

[23] See, for instance, Alexander (1961) and Fama and Blume (1966).

substantially weakened when the survivorship bias is corrected. Ready (2002) argues that the apparent success of the Brock *et al.* (1992) moving average rules is a spurious result of datasnooping, which occurs when a given set of data is used more than once for purposes of inference or model selection.

Despite the academic controversy over the merits of technical trading rules, they are one of the most widely used forecasting techniques among market practitioners as mentioned by Billingsley and Chance (1996) who note that 70% of the Commodity Trading Advisors (CTAs) are trend followers and tend to trade in a similar manner. The heavy use of technical trading rules by futures and currency funds has also been documented from a technical perspective. For instance, Jensen (2003) replicates, with a 75% correlation, the typical managed-futures hedge fund (represented by the CSFB/Tremont managed futures index) with a basic 1-month and 3-month moving average trading strategy applied to the major futures markets. Lequeux and Acar (1998) form a dynamic currency index (AFX), based on the performance of 3 simple moving averages, which exhibit similar performance to currency traders' benchmarks.

Market volatility has an impact on futures trading, for instance, Pan *et al.* (2003) study the influence of volatility on futures trading and find that an increase in volatility motivates traders to engage in more trading in futures markets. In addition, volatility filters have been proposed to improve the overall performance of trend-following systems because trend-following systems are known to perform poorly when markets become volatile. Roche and Rockinger (2003) explain that high volatility periods often correlate with periods when prices change direction, and therefore propose to reverse the technical signals generated when market volatility is forecast to be higher than a chosen threshold. Dunis and Chen (2005) argue that MACD models perform poorly in volatile markets, precisely because volatile markets imply frequent direction changes, and thus introduce a volatility filter which stops trading at times of high volatility.

3.3 Technical Trading Rules: the Methodology

3.3.1 MACD

Technical trading rules have long been applied in financial markets, and these rules are still one of the most popular techniques applied by market practitioners. A technical trending system is built based on the basic assumption that "everything is in the rate and the market moves in trend". Then the major task of such a trend-following system is to define the prevailing trend and to identify early reversals.

One of the most widely used technical trending systems is the moving average convergence and divergence system (MACD). An MACD crossover system consists of two moving averages (MA), a short-term MA and a long-term MA, of the underlying financial series. For the daily data, we use "s D - l D" to refer to a specific MACD, where s and l are the number of days in the short-term and long-term MA respectively, while for the monthly data it is "s M - l M" accordingly. In such a system, the long-term MA is to identify the prevailing trend, and the short-term functions as the market timing device. The trading strategy based on an MACD system is to go long (or short) when the short-term MA is above (or below) the long-term MA. The idea behind MAs is to smooth out a volatile time series and there are many ways to compute MAs. We use the simple MA where all past observations are assigned equal weights as:

$$MA_{(t)} = (1/n)\sum_{i=1}^{n} p_{t-i} \tag{3.1}$$

3.3.2 Trend-Following Technique and Market Volatility

Following chapter 2, we use the time-varying RiskMetrics volatility model to measure the conditional market volatility and amend our trend-following models when a given level of conditional volatility has been breached. RiskMetrics is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \tag{3.2}$$

where σ^2 is the volatility forecast of a specific asset, r^2 is the squared return of that asset, and μ = 0.94 for daily data and 0.97 for monthly data as computed in JP Morgan (1994)[24].

[24] The assumption is that the mean of asset return r is zero so that $r^2_{(t)}$ represents the latest variance. In addition, at the beginning to initiate the computation, we set $\sigma^2_{(0)} = r^2_{(0)}$

3.3.3 Volatility Filter Rules

As described in the previous chapter, we use the symbol $MA^{(p)}{}_{(t+1,t)}$ to denote the trading signals from an MACD model at time t for time $t+1$, where p is the volatility filter imposed on that model: p takes the value of 0 if there is no volatility filter, it takes the value of 1 when the "no-trade" filter is used and 2 when a "reverse" filter is in use.

3.3.3.1 "No-trade" Strategy

Since MACD models are found to perform poorly in volatile markets, following chapter 2, the "no-trade" volatility filter rule proposed is to stay out of the market when the underlying volatility is forecast to be higher than a certain threshold T. The previous MACD trading rules are thus combined with the "no-trade" strategy:

$$MA^{(1)}{}_{(t+1,t)} = \begin{cases} MA^{(0)}{}_{(t+1,t)} & \sigma^2{}_{(t+1,t)} < T \\ 0 & \sigma^2{}_{(t+1,t)} > T \end{cases}$$

3.3.3.2 "Reverse" Strategy

As in chapter 2, a "reverse" filter is proposed to reverse the signals generated when market volatility is forecast to be higher than a chosen threshold:

$$MA^{(2)}_{(t+1,t)} = \begin{cases} MA^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ -\left(MA^{(0)}_{(t+1,t)}\right) & \sigma^2_{(t+1,t)} > T \end{cases}$$

3.4 Data and Dynamic Portfolios

The entire sample period is from 02/01/1998 to 31/12/2004 (1814 observations for daily data and 84 observations for monthly data) and all datasets used are daily and monthly closing prices obtained from Datastream. We use data of the first year of the databank for MACD calculation and volatility measurement initialisation, and we just select those MACD parameters that are popular in the market without making the effort to use a lot of "in-sample" data to optimise model parameters, the whole period for performance measurement purposes is from 04/01/1999 to 31/12/2004 (1556 observations for daily data and 72 observations for monthly data). To measure the consistency of those performance measures, we split the entire performance period into 3 periods: i.e. the full 6-year period (04/01/1999 - 31/12/2004), the last 4-year period (02/01/2001 - 31/12/2004) and the last 2-year period (02/01/2003 - 31/12/2004).

The daily (monthly) asset returns r in time period t are calculated as the percentage change of the daily (monthly) closing value p:

$$r_t = \left(\frac{p_t - p_{t-1}}{p_{t-1}}\right) \tag{3.3}$$

3.4.1 Futures Portfolio

The major objective of this chapter is to apply volatility filters to two portfolios that replicate the performance of average futures and currency traders.

Table 3.1 Asset allocation and dynamic MACD strategy for the futures portfolio

Assets (Futures)	EUR$ (CME)	T-Note (CBT)	S&P500 (CME)	EUR/USD (CME)	USD/JPY (CME)	GBP/USD (CME)	Copper (COMEX)
Weights	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%	14.29%
MACD Strategy (daily data)	1D - 250D	1D - 250D	3D - 250D	1D - 61D	1D - 61D	1D - 61D	1D - 250D
MACD Strategy (monthly data)	1M - 12M	1M - 12M	1M - 12M	1M - 3M	1M - 3M	1M - 3M	1M - 12M

Jensen (2003) replicates the typical managed futures hedge fund with a basic 1-month by 3-month moving average trading strategy applied to Eurdollar (EUR$), S&P500, US T-note, EUR/USD and USD/JPY futures markets, while in this chapter we add two more assets, GBP/USD and Copper to expand the asset coverage while at the same time retaining a high correlation level. The contracts included in the futures portfolio are EUR$ (CME), T-Note (CBT), S&P500 (CME), EUR/USD (CME), USD/JPY (CME), GBP/USD (CME) and Copper (COMEX) as shown in table 3.1. The 7 futures assets are all U.S. contracts with reasonably similar closing times. The equally weighted portfolio has been constructed on a trial and error basis to highly correlate with the CSFB/Tremont managed futures performance index.

For daily data, the MACD specifications are those MACDs that are widely used by market practitioners. The futures portfolio formed in this way is highly correlated with the CSFB/Tremont managed futures index. Calculated from January 1994, the CSFB/Tremont hedge fund index is the industry's leading asset-weighted hedge fund index. There are also 10 sub-indices that represent the performance of the 10 primary hedge fund subcategories based on their investment style. CSFB/Tremont analyses the percentage of assets invested in each subcategory and selects funds for the index based on those percentages. For our purpose here, we analyse the CSFB/Tremont managed futures sub-index. Since all CSFB/Tremont indices are computed on a monthly basis, we also use monthly data with monthly MACD specifications. Bearing in mind that the lowest time span with monthly data will be 1 month, we try to replicate the time span of the daily MACD for the longer term moving average: for instance, a 1D-61D daily MACD for the EUR/USD series is approximated by a 1M-3M monthly MACD. Daily and monthly MACD specifications as well as asset allocation weights for the futures portfolio can be found in table 3.1. With this approach, both the daily and monthly dynamic futures portfolios are highly correlated with the CSFB/Tremont managed futures index for the 6-year, 4-year and 2-year periods. This futures portfolio is then able to replicate the typical managed futures funds in the market (see figure 3.1).

Table 3.2 suggests consistency across the different periods under review[25]. The fact that the dynamic portfolio represents the performance of managed

[25] Since the CSFB/Tremont managed futures index is only available on a monthly basis, to find the correlation between the index and the futures portfolio with daily data, we sum the daily returns in each month to form a series of aggregated monthly returns with which the correlation to the index is calculated.

futures funds is not only supported by its consistent and high correlation to the CSFB/Tremont managed futures index correctly over time. It is also confirmed by the closeness of both risk-adjusted information ratios (see table 3.4), even if the dynamic portfolio has a lower return and a lower volatility compared to the CSFB/Tremont index, and this is due to the fact that most futures funds are leveraged.

Figure 3.1 Correlation between CSFB/Tremont managed futures index and the futures portfolios

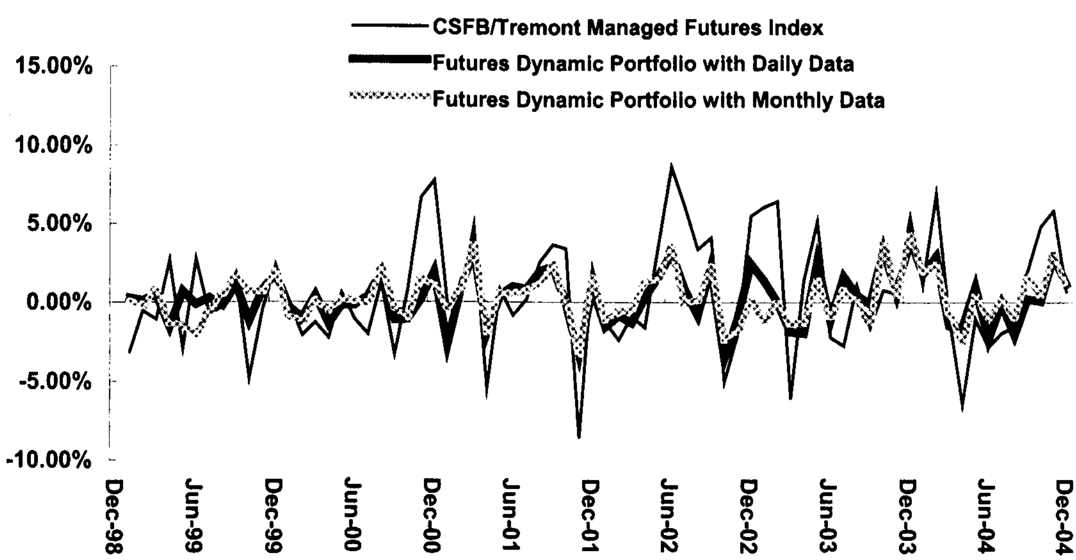


Table 3.2 Coefficient of correlation between CSFB/Tremont managed futures index and the futures portfolios

	6-year Period	4-year Period	2-year Period
Futures Portfolio (aggregate monthly return with daily data)	0.68	0.71	0.64
Futures Portfolio (monthly data)	0.62	0.69	0.58

3.4.2 FX Portfolio

Lequeux and Acar (1998) introduce a dynamic currency index (AFX index) to replicate the performance of the typical currency fund managers. The index consists of 7 currency futures rates using 3 simple MACD (namely 1D-32D, 1D-61D and 1D-117D) strategies with each MACD taking the same weight in generating trading signals. They find that the AFX index has high correlation with and low tracking error to currency traders' performance. Following the same 1D-32D, 1D-61D and 1D-117D MACD combination strategy, we form the FX portfolio using currency spot rates since trading volumes in the FX spot market are much bigger than those in the futures market. We also expand the portfolio composition to include the 9 most heavily traded major exchange rates according to the recent BIS FX trading survey[26] (they represent over 78% of the USD 1.8 trillion daily FX turnover reported for April 2004) and update the portfolio-weighting scheme using the data from this survey (BIS 2004)[27].

Table 3.3 FX portfolio currency allocation

Currency	EUR /USD	USD /JPY	GBP /USD	USD /CHF	USD /CAD	AUD /USD	EUR /GBP	EUR /JPY	EUR /CHF
Weights	35.76%	21.13%	17.49%	5.57%	5.07%	6.42%	3.07%	3.64%	1.85%

Both the asset combination and weights of the FX portfolio are shown in table 3.3. It should be noted that for simplicity in this chapter all FX currency

[26] We use the notation of the International Organisation for Standardisation (IOS) for all the exchange rates considered.
[27] As for chapter 2 (see footnote 13), the asset allocations set for all the portfolios in this chapter remain unchanged for the entire data sample period.

returns are exclusive of interest income or payments for holding a specific currency: these could further enhance the models performance displayed throughout, but as our objective in this chapter is to compare the relative performance of the FX portfolio with and without volatility filters, the exclusion of interest income or payments can be ignored.

3.5 Empirical Results

The entire performance period for both the futures and FX portfolio is split into 3 periods to measure the consistency of the trading performance over different periods of time. Model performance statistics for the 2 portfolios can be found in table 3.4.

3.5.1 Results for the Futures Portfolio

Not only does the futures portfolio with the dynamic daily MACD strategy highly correlate with the CSFB/Tremont managed futures index, but it also produces similar information ratios to those from the index for all the 3 periods, which confirms that this portfolio can consistently replicate the performance of the typical managed futures funds. For the futures portfolio with daily data, the addition of either the "no-trade" or the "reverse" filter brings a significant improvement in terms of annualised return and the risk-adjusted information ratio in all the 3 periods. In the longer term 6-year period, the "reverse" strategy increases the annualised return from 3.06% to 5.47%, while on the other hand the "no-trade" strategy lowers the maximum drawdown successfully with improving the annualised return at the same time. More such significant improvements on major performance measures are also found over the recent 4-year and 2-year periods. The risk-adjusted information ratios obtained from strategies using the filters are also high, which suggests that the performance results obtained with the volatility filters are not only good when compared to the portfolio without filters, they are also actionable in a trading environment. As far as the two filters are concerned, the "reverse" filter strategy performs better than the "no-trade" filter strategy in terms of annualised return and risk-adjusted measures. With a "no-trade" strategy, investors are able to free funds out of a highly volatile market and into other less turbulent markets (for instance, short-term money deposits) which might further increase yield and reduce risk. From this perspective there is no real "winning" filter and it is up to investors to choose the right strategy based on their risk tolerance. But it is obvious that markets behave differently at high volatility levels and adaptive strategies like the ones suggested should be adopted during those periods.

Since the CSFB/Tremont index is computed on a monthly basis, we also apply the same asset composition and weighting scheme using monthly data with the MACD strategies approximated as mentioned before: i.e. a 1D-61D daily MACD for the EUR/USD series is approximated by a 1M-3M monthly MACD. It is found that the portfolio with monthly data is highly correlated with the CSFB/Tremont index as well. Again the addition of the two filters adds value to the models performance in terms of annualised return and risk-adjusted information ratios. The "reverse" strategy seems to outperform on most performance measures most of time, while the "no-trade" strategy

Table 3.4 Performance statistics

Futures Portfolio (Aggregate Monthly Return With Daily Data)	*6-year Period (04/01/99-31/12/04)* CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter	*4-year Period (02/01/01-31/12/04)* CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter	*2-year Period (02/01/03-31/12/04)* CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter
Correlation to CSFB/Tremont	1	0.68	0.69	0.67	1	0.71	0.73	0.72	1	0.64	0.63	0.62
Annualised Return	6.97%	3.06%	4.26%	5.47%	10.37%	4.13%	5.53%	6.93%	10.40%	5.77%	6.57%	7.37%
Cumulative Return	41.82%	18.38%	25.59%	32.79%	41.47%	16.54%	22.12%	27.71%	20.80%	11.54%	13.14%	14.73%
Annualised Volatility	12.51%	5.74%	5.53%	5.51%	13.47%	6.60%	6.32%	6.22%	13.32%	6.48%	6.28%	6.18%
Maximum Drawdown	-14.69%	-6.59%	-5.53%	-4.88%	-14.69%	-6.59%	-5.53%	-4.88%	-14.69%	-6.59%	-5.37%	-4.85%
Information Ratio	0.56	0.53	0.77	0.99	0.77	0.63	0.88	1.11	0.78	0.89	1.05	1.19

Futures Portfolio (Monthly Data)	CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter	CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter	CSFB/ Tremont	Futures Portfolio	No-trade Filter	Reverse Filter
Correlation to CSFB/Tremont	1	0.62	0.59	0.52	1	0.69	0.67	0.62	1	0.58	0.53	0.41
Annualised Return	6.97%	3.42%	3.94%	4.45%	10.37%	4.71%	4.75%	4.79%	10.40%	5.31%	5.39%	5.47%
Cumulative Return	41.82%	20.54%	23.62%	26.70%	41.47%	18.83%	18.99%	19.15%	20.80%	10.63%	10.79%	10.95%
Annualised Volatility	12.51%	5.26%	5.06%	5.15%	13.47%	5.86%	5.57%	5.64%	13.32%	5.93%	5.34%	5.48%
Maximum Drawdown	-14.69%	-7.89%	-7.89%	-7.89%	-14.69%	-7.89%	-7.89%	-7.89%	-14.69%	-4.62%	-3.26%	-2.81%
Information Ratio	0.56	0.65	0.78	0.86	0.77	0.80	0.85	0.85	0.78	0.90	1.01	1.00

FX Currency Portfolio (Daily Data)	FX Portfolio	No-trade Filter	Reverse Filter	FX Portfolio	No-trade Filter	Reverse Filter	FX Portfolio	No-trade Filter	Reverse Filter
Annualised Return	1.60%	3.12%	4.63%	0.57%	2.37%	4.16%	1.25%	2.22%	3.19%
Cumulative Return	9.90%	19.24%	28.59%	2.37%	9.77%	17.17%	2.61%	4.62%	6.63%
Annualised Volatility	5.62%	4.81%	5.00%	5.59%	4.88%	4.98%	5.71%	5.13%	5.14%
Maximum Drawdown	-14.09%	-11.70%	-9.30%	-14.09%	-11.70%	-9.30%	-14.09%	-11.70%	-9.30%
Information Ratio	0.29	0.65	0.93	0.10	0.48	0.83	0.22	0.43	0.62

performs only marginally better in terms of information ratio for the more recent 2-year period. Not surprisingly, with fewer trades (as a matter of fact, the strategy with monthly data assumes that trades are only executed at the end of each month), the portfolio with monthly data has lower annualised return and annualised volatility. As far as trading frequency is concerned, for EUR/USD and Bond futures, where the same MACD specifications are adopted, the trading frequencies on average for both series are about 14 times a year for daily data and 7 times a year for monthly data. In addition, with longer time spans in the MACD specification, the trading frequency for S&P500 futures is lower, about 3 times a year for daily data and twice a year for monthly data. When transaction costs are taken into account, the portfolio with daily data significantly outperforms the one with monthly data most of the time in terms of risk-adjusted measures. This suggests that a close watch on the markets and active trading may pay back in the futures market.

3.5.2 Results for the FX portfolio

Similar results have been found for the FX portfolio performance, with the addition of either filters adding value to model performance on all major measures for the 3 periods considered. In the longer 6-year period, improvements on both the return and risk in terms of annualised return and maximum drawdown are found with the addition of either filter. What is more, the "reverse" strategy is very successful in generating returns from taking opposite positions to the original signals in volatile markets, so it prevails over the "no-trade" strategy in all cases in terms of risk-adjusted measures.

3.6 Concluding Remarks

Technical trading rules are known to perform poorly in periods when volatility is high. The objective of this chapter was to relate our findings from chapter 2 to the real business world and to study whether the addition of volatility filters can improve model performance of average market players. Two portfolios, which are highly correlated with a managed futures index and a currency traders' performance benchmark, were formed to replicate the performance of the typical managed futures and managed currency funds. The volatility filters proposed were applied directly to the two portfolios with the belief that the proposed techniques which perform well on these portfolios have both academic and industrial significance.

The specifications of the MACDs used in the two dynamic portfolios are the ones commonly applied in the market instead of any other number arbitrarily selected. The futures portfolio, which is highly correlated with the CSFB/Tremont managed futures index, is devised to mimic the performance of the typical managed futures funds. Following the Lequeux and Acar (1998), we also form an FX portfolio using the 9 most heavily traded FX spot rates to replicate typical currency funds. Two volatility filters were proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from a simple MACD are reversed if market volatility is higher than a given threshold.

Our results show that the two volatility filters significantly improve the performance of both portfolios in terms of all major performance measures in all the 3 periods considered. For instance, in the longer 6-year period, the "reverse" strategy increases the annualised return from 3.06% to 5.47% for the futures portfolio using daily data and from 1.60% to 4.63% for the currency FX portfolio. Significant improvements on market risk in terms of annualised volatility and maximum drawdown are also found with the filters imposed. The results are believed to be consistent as significant improvements are also found over the more recent 4-year and 2-year periods. These results confirms with the findings from chapter 2. In addition, the information ratios obtained from strategies using the filters are also high, suggesting that the performance results obtained with volatility filters are not only good in relative terms when compared to the portfolios without filters, they are also actionable in a trading environment.

Although the "reverse" strategy outperforms in terms of risk-adjusted measures most of the time, investors following a "no-trade" strategy are able to free up funds out of highly volatile markets and invest into other markets for short-term profits. In this respect, there is no "winning" of one filter against the other and it is up to investors to choose the right strategy based on their risk tolerance. But it is obvious that markets behave differently at high volatility levels and adaptive strategies like those proposed need to be adopted during such periods.

Finally, with fewer trades the futures portfolio using monthly data has low annualised returns and annualised volatility. The portfolio with daily data significantly outperforms the one with monthly data most of the time in terms of risk-adjusted measures even when transaction costs are taken into account. This suggests that a close watch on the markets and active trading may pay back in the futures market.

CHAPTER 4

Volatility Filters for FX Portfolios Trading:

The Impact of Alternative Volatility Models

Chapter Overview

In both chapter 2 and 3, we find that the addition of volatility filters with RiskMetrics forecasts can improve the performance of moving average convergence and divergence (MACD) models. The motivation of this chapter is to test whether alternative volatility models forecasts can further improve the MACD models performance with such filters.

The two alternative volatility forecast models used in this chapter are GARCH model as in Bollerslev (1986) and stochastic volatility model with Markov switching (MS) based on Hamilton (1994) and Roche and Rockinger (2003).

Our results show that volatility filters using alternative volatility models fail to enhance the performance of the simpler filters using RiskMetrics forecasts in terms of annualised return and information ratio.

4.1 Introduction

The volatility of foreign exchange (FX) rates has always been of particular interest to both academic researchers and market investors since the breakdown of the Bretton Woods system in 1971-73. With the introduction of currency derivatives, modelling and forecasting FX volatility, which is the key variable in option pricing, has become even more important. An accurate valuation of currency options from the best prediction of FX volatility is crucial to hedge FX exposures and/or speculate in currency markets.

Before the seminal paper by Engle (1982), the uncertainty of FX rates was measured by the sample variances and covariances calculated over a recent sample period. This traditional measure of volatility is challenged as the returns exhibit leptokurtosis and volatility is known to be clustering. Engle (1982) ARCH model and Bollerslev (1986) GARCH model are designed specifically to model these changes in volatility. There are many papers supporting the use of GARCH model[28]. Alternatively, the so-called conditional volatility may also be modeled as an unobserved component following a stochastic process. The resulting stochastic volatility models have also encountered great success (See Taylor 1994, Breidt *et al.* 1998, Roche and Rockinger 2003, Billio and Sartore 2003).

Most of fund managers in the currency markets are technical traders, and

[28] See, among others, Akgiray (1989), Bollerslev *et al.* (1992), Pagan and Schwert (1990), West and Cho (1995) and Chong *et al.* (1999)

Billingsley and Chance (1996) mention that 70% of the Commodity Trading Advisors (CTAs) are trend followers and tend to trade in a similar manner. Trend-following systems are known to perform poorly when markets are very volatile. We find previously that the addition of volatility filters can improve the performance of the moving average convergence and divergence (MACD) models that replicate typical currency fund managers as introduced by Lèqueux and Acar (1998). In the previous 2 chapters and Miao and Dunis (2005), RiskMetrics is used to model and forecast the time-varying volatility. The motivation of this chapter is to test whether using alternative volatility models forecasts can further improve the model performance using volatility filters.

The two alternative volatility forecast models used in this chapter are the GARCH model of Bollerslev (1986) and a stochastic volatility model with Markov switching (MS). Following chapter 2 and 3, two volatility filters are proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from a simple model are reversed if the market volatility is higher than a given threshold.

Our results show that in the out-of-sample period, addition of either a "no-trade" or a "reverse" volatility filter using alternative volatility forecasts fails to outperform the model with such volatility filters using RiskMetrics forecasts. However, whatever volatility forecasts are used, the addition of volatility filters can significantly outperform the original MACD model in both the in-sample and out-of-sample periods, which confirms the findings from the previous 2 chapters.

The rest of the chapter is organized as follows: section 4.2 describes the data used and the FX portfolio formed, and section 4.3 explains the volatility models and the volatility filter rules. Section 4.4 presents the empirical results, focusing on the out-of-sample models performance, followed by concluding remarks in section 4.5.

4.2 Data and the FX Portfolio

Lequeux and Acar (1998) introduce a dynamic currency index (AFX index) to replicate the performance of typical currency fund managers. The index consists of 7 currency futures rates using 3 simple MACD strategies (namely 1 and 32-day, 1 and 61-day and 1 and 117-day) with each MACD taking the same weight in generating trading signals. They find that the AFX index has a high correlation and low tracking error with the performance of typical currency fund managers. Following the same MACD combination strategy, we form our benchmark FX portfolio using currency spot rates since trading volumes in the FX spot market are much higher than those in the futures market. We also expand the portfolio composition to include the 9 most heavily traded major exchange rates according to the recent BIS FX trading survey[29] (they represent over 78% of the USD 1.8 trillion daily FX turnover reported for April 2004) and update the portfolio-weighting scheme using the data from this survey (BIS 2004). Both the asset combination and weights of

[29] We use the notation of the International Organisation for Standardisation (IOS) for all the exchange rates considered.

the FX portfolio are shown in table 4.1[30].

Table 4.1 FX portfolio currency allocation

Currency	EUR /USD	USD /JPY	GBP /USD	USD /CHF	USD /CAD	AUD /USD	EUR /GBP	EUR /JPY	EUR /CHF
Weights	35.76%	21.13%	17.49%	5.57%	5.07%	6.42%	3.07%	3.64%	1.85%

The entire sample period is from 02/01/1998 to 31/05/2005 with 1921 days of observations and all datasets used are daily closing prices in London obtained from Datastream[31]. The entire sample period is divided into 2 periods: the dataset from 02/01/1998 to 31/05/2004 with 1660 days of observations as the in-sample period, and the remaining 261 observations as out-of-sample period.

The daily currency returns *r* in time period *t* are calculated as the percentage change of the daily currency rate *p*:

$$r_t = \left(\frac{p_t - p_{t-1}}{p_{t-1}}\right) \qquad (4.1)$$

4.3 Volatility Models and Volatility Filter Rules: the Methodology

[30] As for chapter 2 (see footnote 13), the asset allocation set for the FX portfolio in this chapter remains unchanged for the entire data sample period.
[31] Since the 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 02/01/1998 to 31/12/1998 combining the spot USD/DEM and the fixed EUR/DEM exchange rate. The synthetic EUR/GBP, EUR/JPY and EUR/CHF are created following the same approach.

4.3.1 GARCH Models

The ARCH model of Engle (1982) has been seen as a revolution in modelling and forecasting volatility. It was further generalised by Bollerslev (1986) as the GARCH model. The GARCH type models assume that volatility changes over time in an autoregressive manner.

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{4.2}$$

where h_t is the conditional variance which is expressed as a function of a constant, the previous periods squared random component of the return and the previous periods' variance. In our study, we tried alternative models for in-sample fitting, and the model parameters are selected based on AIC/SBC criteria. The GARCH models estimation output tables can be found in appendix A.16-A.24, where it can be seen that all ARCH and GARCH coefficients are statistically significant.

4.3.2 RiskMetrics Model

The RiskMetrics volatility can be seen as a special case of Bollerslev (1986) GARCH model with pre-determined decay parameters, and it is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \tag{4.3}$$

where σ^2 is the volatility forecast of a specific asset, r^2 is the squared return of that asset, and $\mu = 0.94$ for daily data as computed in JP Morgan (1994)[32].

4.3.3 Stochastic Volatility with Markov Switching

One of the main findings of empirical studies on volatility is that the volatility of asset returns tends to change stochastically over time (Psychoyios *et al.* 2003). Hamilton (1989) proposes a stochastic volatility model with Markov switching, which has received great attention. With such a model, asset returns are assumed to be a mixture of distributions and the regime changes between these distributions follow a Markovian process. The stochastic volatility model we use in this model is based on Hamilton (1994) and Roche and Rockinger (2003): the model only allows the variance to switch, and it assumes returns are a mixture of normal distributions as in equation (4.4) below.

$$R_t = \mu + [\sigma_1 S_t + \sigma_0 (1 - S_t)]\varepsilon_t \tag{4.4}$$

where ε_t are independent and identically distributed normal distributions with mean 0 and variance 1. S_t is a Markov chain with values 0 and 1 and with transition probabilities $p=[p_{00}, p_{01}, p_{10}, p_{11}]$ such that:

p_{11} = Pr[St=1/St-1=1]

p_{01} = Pr[St=0/St-1=1]

p_{10} = Pr[St=1/St-1=0]

p_{00} = Pr[St=0/St-1=0]

---

32 The assumption is that the mean of asset return r is zero so that $r^2_{(t)}$ represents the latest variance. In addition, at the beginning to initiate the computation, we set $\sigma^2_{(0)} = r^2_{(0)}$

where $p_{11}+p_{01}=1$ and $p_{10}+p_{00}=1$

If we assume that ε_t follow normal distribution, the density function of R_t conditional on regime S_t, f (R_t / S_t) can be written as:

$$f(R_t / S_t) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_1 S_t + \sigma_0(1-S_t)} \exp\left\{-\frac{1}{2}\left(\frac{R_t - \mu}{\sigma_1 S_t + \sigma_0(1-S_t)}\right)^2\right\} \qquad (4.5)$$

The likelihood function to be maximized is:

$$L = f(R_t) = f(R_t / R_{t-1}) f(R_{t-1} / R_{t-2}) \cdots f(R_2 / R_1) f(R_1) \qquad (4.6)$$

Moreover:

$$f(R_t / R_{t-1}, S_t) = \sum_{S_t=0}^{1} f(R_t, S_t) \Pr[S_t / R_{t-1}] \qquad (4.7)$$

$$\Pr[S_t / R_{t-1}] = \sum_{S_{t-1}=0}^{1} \Pr[S_t / S_{t-1}] \Pr[S_{t-1}, R_{t-1}] \qquad (4.8)$$

$$\Pr[S_{t-1} / R_{t-1}] = \frac{f(R_{t-1} / S_{t-1}) \Pr[S_{t-1} / R_{t-2}]}{\sum_{S_{t-1}=0}^{1} f(R_{t-1} / S_{t-1}) \Pr[S_{t-1} / R_{t-2}]} \qquad (4.9)$$

It is now quite simple to compute $\Pr[S_t / R_{t-1}]$ from equation (4.8) and equation (4.9) for all time t following a recursive approach. It should be noted that the starting value of $\Pr[S_t=1]$ and $\Pr[S_t=0]$ can be either estimated directly as additional parameters, or approximated by the steady state probabilities as:

$$\Pr[S_t = 1] = \frac{1 - p_{00}}{2 - p_{11} - p_{00}} \qquad (4.10)$$

$$\Pr[S_t = 0] = \frac{1 - p_{11}}{2 - p_{11} - p_{00}} \tag{4.11}$$

The estimation of the MS model is programmed using Maximum Likelihood Objects with Eviews. Within the program, the corresponding coefficients are:

$$\sigma_1 = C(1)$$

$$\sigma_0 = C(2)$$

$$\mu = C(3)$$

$$\rho_{11} = \frac{C(4)}{1 + C(4)}$$ [33]

$$\rho_{00} = \frac{C(5)}{1 + C(5)}$$

The MS models estimation output tables can be found in appendix A.25-A.33, where it can be seen that all coefficients are statistically significant except for the mean μ.

4.3.4 MACD and Volatility Filter Rules

4.3.4.1 MACD Trading Strategy

A MACD system consists of two moving averages (MAs), a short-term MA and a long-term MA, of the underlying asset. In such a system, the long-term MA is used to identify the prevailing trend, and the short-term is a market timing device. The trading strategy based on a MACD system is to go long (or short) when the short-term MA is above (or below) the long-term MA. The idea behind the use of MAs is to smooth out a volatile time series and there

[33] The use of Logit equation is to ensure that p_{11} and p_{00} lie between [0,1].

are different ways to compute MAs. We use the simple MA where all past observations in the MA are assigned an equal weight as:

$$MA_{(t)} = (1/n)\sum_{i=1}^{n} p_{t-i} \tag{4.12}$$

Following Lequeux and Acar (1998), we generate the MACD trading signals using 3 simple MACD strategies (namely 1 and 32-day, 1 and 61-day and 1 and 117-day) with each MACD taking the same weight.

We find above in chapter 2 and 3 that returns generated from MACD signals become negative most of the time when a market experiences high volatility. This suggests that a different strategy might be adopted when the volatility regime changes. We use the symbol $MA^{(p)}{}_{(t+1,t)}$ to denote the trading signals from an MACD model at time *t* for time *t+1*, where the superscript *p* is the volatility filter imposed on that model: *p* takes the value of 0 if there is no volatility filter, it takes the value of 1 when a "no-trade" filter is used and 2 when a "reverse" filter is selected.

4.3.4.2 "No-trade" Strategy

Since MACD models are found to perform poorly in volatile markets, following chapter 2, the "no-trade" volatility filter rule proposed is to stay out of the market when the underlying volatility is forecast to be higher than a certain threshold T. A simple trading rule combined with a "no-trade" filter can be expressed as:

$$MA^{(1)}_{(t+1,t)} = \begin{cases} MA^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ 0 & \sigma^2_{(t+1,t)} > T \end{cases}$$

4.3.4.3 "Reverse" Strategy

As in chapter 2, a "reverse" filter proposed is to reverse the signals generated when market volatility is forecast to be higher than a chosen threshold:

$$MA^{(2)}_{(t+1,t)} = \begin{cases} MA^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ -\left(MA^{(0)}_{(t+1,t)} \right) & \sigma^2_{(t+1,t)} > T \end{cases}$$

4.4 Empirical Results

In this study, we follow Lequeux and Acar (1998) to set the transaction cost as 0.03% per round-trip transaction for all currency rates in the portfolio. Performance measures after the deduction of transaction costs are shown in table 4.2. It should be noted that for simplicity in this chapter all FX currency returns are exclusive of interest income or payments for holding a specific currency: these could further enhance the models performance displayed throughout, but as our objective in this chapter is to compare the relative performance of volatility filters using different volatility model forecasts, the exclusion of interest income or payments can be ignored.

In the out-of-sample period, when the "no-trade" filter is imposed, the model with volatility filters using RiskMetrics forecasts outperforms the other two models using GARCH and MS volatility forecasts in terms of annualised return and risk-adjusted information ratio. Similar results can be seen when the "reverse" filter is imposed. This suggests that the use of RiskMetrics can well capture the advantage of volatility filters, and using different volatility model forecasts does not really improve the models performance. This better performance of the RiskMetrics approach may be linked to its general applicability, whereas the GARCH and MS model parameters have been estimated over a 6-year period and then used for out-of-sample simulation for a whole year without re-estimation. In addition, models performance with GARCH forecasts seems better than that with MS volatility forecasts. It is

Table 4.2 Performance statistics for FX portfolio

In-Sample Performance (02/01/98-31/05/04)

	Without Filter	No-Trade Filter			Reverse Filter		
		RiskMetrics	**GARCH**	**MS Model**	**RiskMetrics**	**GARCH**	**MS Model**
Annualised Return	3.03%	3.50%	3.33%	4.97%	3.69%	3.38%	6.71%
Annualised Volatility	5.49%	4.11%	4.51%	4.86%	4.65%	4.49%	4.92%
Information Ratio	0.55	0.85	0.74	1.02	0.79	0.75	1.36

Out-of-Sample Performance (01/06/04-31/05/05)

	Without Filter	No-Trade Filter			Reverse Filter		
		RiskMetrics	**GARCH**	**MS Model**	**RiskMetrics**	**GARCH**	**MS Model**
Annualised Return	-5.32%	-4.30%	-4.54%	-5.25%	-3.38%	-3.91%	-5.20%
Annualised Volatility	4.96%	4.88%	4.68%	4.95%	4.87%	4.64%	4.95%
Information Ratio	-1.07	-0.88	-0.97	-1.06	-0.69	-0.84	-1.05

worth noting that all strategies recorded losses over the out-of-sample period. Yet, this was also the case of the AFX dynamic currency index which recorded a loss of 3.19% over the same period before the deduction of transaction costs.

Our results also show that in both the in-sample and out-of-sample period, the addition of volatility filters using alternative volatility forecasts improves on the original MACD models without filters in all cases. It is also found that the performance differences between the “no-trade” and “reverse” filters are marginal, implying that neither filter is significantly prevailing over the other.

4.5 Concluding Remarks

The major objective of this chapter was to compare the performance of volatility filters using different volatility forecasts when such filters are imposed on dynamic MACD models that replicate typical currency traders as in Lequeux and Acar (1998). Our results show that alternative volatility models to RiskMetrics fail to enhance performance in terms of annualised return and information ratio. In addition, in both in-sample and out-of-sample periods, the addition of the two volatility filters retained using the three volatility forecasts improves on the original MACD models studied. Empirically, this confirms the findings from chapter 2 and chapter 3.

PART TWO

Volatility Filters for Alternative Trading Rules

CHAPTER 5

Trading Foreign Exchange Portfolios with Volatility Filters: The Carry Model Revisited

Chapter Overview

The rejection of the simple risk-neutral efficient market hypothesis in the foreign exchange (FX) market opens the possibility of the profitable use of a carry model taking full advantage of interest rate differentials to trade currencies. A first motivation for this chapter is to study whether a simple passive carry model can outperform a typical currency fund manager replicated by dynamic technical moving average convergence and divergence (MACD) models as in Lequeux and Acar (1998). Secondly, following the findings from chapter 2 and 3 that volatility confirmation filters can improve performance of MACD models which perform poorly in times of volatile markets, we study whether the addition of such volatility filters can help to improve the carry model performance.

We consider the period starting from the introduction of the Euro (EUR) on 04/01/1999. Our results show that the simple carry model performs much better than the benchmark MACD model, while a combined carry/MACD model has the lowest trading volatility. Moreover, the addition of two volatility filters adds significant value to the performance of the three models studied.

5.1 Introduction

Under the simple risk-neutral efficient market hypothesis, the forward rate is the best unbiased forecast of the future spot rate and equivalently the forward premium (resp. discount) is the optimal predictor of a currency appreciation (resp. depreciation). Numerous articles have tested this hypothesis and there is now a wide consensus that the simple risk-neutral efficient market hypothesis can be rejected (see, for instance, Clarida and Taylor 1997). Yet a parallel finding in the foreign exchange (FX) literature is that empirical exchange rate models cannot outperform a simple random walk forecast (see, for instance, Meese and Rogoff 1983a, b).

If the actual exchange rate change is not equal to the interest rate differential as suggested by the simple risk-neutral efficient market hypothesis, and the future spot exchange rates are not forecastable, a simple trading strategy would therefore be just to take advantage of interest rate differentials. Largely known (and implemented) as "carry trading" by currency fund managers, this carry strategy entails to always hold the high yield currency and short the corresponding low yield currency in a currency pair.

The motivation for this chapter is thus twofold. Firstly, we study whether a simple passive carry model (i.e. where new positions are solely triggered by reversals in interest rate differentials) can effectively outperform a typical currency fund manager replicated by dynamic moving average convergence and divergence (MACD) models as in Lequeux and Acar (1998). Moreover, we combine the passive carry model with dynamic MACD models, where the latter operate as a confirmation filter to the former, with an attempt to further enhance performance measures.

Secondly, following the findings from chapter 2 and 3 that volatility confirmation filters can improve performance of MACD models which perform poorly in times of volatile markets, we study whether the addition of such volatility filters can help to improve the carry model performance. Two volatility filters are proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from a simple model are reversed if market volatility is higher than a given threshold.

Our results show that in all the 3 periods considered, when taking transaction costs into account, the simple carry model performs much better than the benchmark MACD model in terms of annualised return, information ratio and maximum drawdown, while the combined carry/MACD model has the lowest trading volatility. Moreover, the addition of the two volatility filters suggested adds significant value to the performance of the three models studied.

The rest of the chapter is organized as follows: section 5.2 briefly reviews the relevant literature, section 5.3 describes the data used and the FX portfolio formed, and section 5.4 documents the carry model and the volatility filters retained. Section 5.5 presents the empirical results, focusing on the models performance during different periods, and is followed by concluding remarks in section 5.6.

5.2 Literature Review

Whether the forward exchange rate is an optimal forecast of the future spot exchange rate is a longstanding question in international finance. In his seminal work on exchange rate theory, Frenkel (1976) notes that "the fundamental relationship that is used in deriving the market measure of inflationary expectations relies on the interest parity theory [which] maintains that in equilibrium the premium (or discount) on a forward contract for foreign exchange for a given maturity is (approximately) related to the interest rate differential. [...] The variations of the forward premium on foreign exchange [...] may be viewed as a measure of the variations in the expected rate of inflation (as well as the expected rate of change of the exchange rate)" (p. 210). Amongst others, Frenkel and Johnson (1978) find empirical evidence that this parity holds. Yet, numerous articles have since shown that the forward rate is not an optimal predictor of the future spot exchange rate (see, for instance, Frankel 1980, Bilson 1981, Taylor 1995 and Wolff 2000). Though rejecting the simple risk-neutral efficient market hypothesis, more recent studies such as Clarida and Taylor (1997) suggest that the term structure of forward premia contains valuable information for forecasting future spot exchange rates.

The predictability of exchange rates has also been the main focus of financial forecasting. So far, a large consensus in the academic literature suggests that exchange rate models cannot outperform a random walk forecast (Clarida *et al.* 2003). For instance, Meese and Rogoff (1983a, b) have clearly shown that predictions of a simple random walk dominate those of standard empirical exchange rate models. Allowing nonlinearity in the exchange rate, Engle and Hamilton (1990) find that out-of-sample forecasts from their segmented-trend models underperform the random walk with drift. More recently, Caporale and Spagnolo (2004) find that for the out-of-sample point forecast results, a nonlinear Markov regime-switching model fails to dominate the random walk model.

This may not mean that small pockets of predictability cannot be extracted successfully with the proper technical tools. Noting that market volatility has an impact on trading, and models like trend-following systems tend to perform poorly when markets become volatile, Roche and Rockinger (2003) explain that high volatility periods often correlate with periods when prices change direction, and therefore propose a successful volatility filter to reverse the technical trading signals generated when market volatility is high. Dunis and Chen (2005) argue that MACD models perform poorly in volatile markets precisely because volatile markets imply frequent direction changes, thus proposing to stop trading at times of high volatility. This chapter relates to this body of literature in the context of the highly liquid FX markets.

5.3 Data and Benchmark FX Portfolio

The entire sample period covers from the introduction of the EUR on 04/01/1999 to 31/03/2005 when all existing positions were closed (1620 daily observations). The exchange rates and 1-month interest rates used are daily closing prices obtained from Datastream. To measure the consistency of performance, we split the entire sample period into 3 periods: the full 6-year period (04/01/1999 - 31/03/2005), the last 4-year period (02/01/2001 - 31/03/2005) and the last 2-year period (02/01/2003 - 31/03/2005).

The daily currency returns *r* for time period *t* are calculated as the percentage change of the daily exchange rate *p*:

$$r_t = \left(\frac{p_t - p_{t-1}}{p_{t-1}}\right) \tag{5.1}$$

Lequeux and Acar (1998) introduce a dynamic currency index (AFX index) to replicate the performance of typical currency fund managers. The index consists of 7 currency futures rates using 3 simple MACD strategies (namely 1 and 32-day, 1 and 61-day and 1 and 117-day) with each MACD taking the same weight in generating trading signals. They find that the AFX index has a high correlation and low tracking error with the performance of typical currency fund managers. Following the same MACD combination strategy, we form our benchmark FX portfolio using currency spot rates since trading volumes in the FX spot market are much higher than those in the futures market. We also expand the portfolio composition to include the 9 most heavily traded major exchange rates according to the recent BIS FX trading survey[34] (they represent over 78% of the USD 1.8 trillion daily FX turnover reported for April 2004) and update the portfolio-weighting scheme using the data from this survey (BIS 2004). Both the asset combination and weights of

[34] We use the notation of the International Organisation for Standardisation (IOS) for all the exchange rates and interest rates considered.

the FX portfolio are shown in table 5.1 below[35].

Table 5.1 Benchmark FX portfolio currency allocation

Currency	EUR /USD	USD /JPY	GBP /USD	USD /CHF	USD /CAD	AUD /USD	EUR /GBP	EUR /JPY	EUR /CHF
Weights	35.76%	21.13%	17.49%	5.57%	5.07%	6.42%	3.07%	3.64%	1.85%

5.4 Carry Model, Conditional Volatility and Filter Rules

5.4.1 Carry Model

The trading strategy for a carry model is to go long in the high yield currency and to short in the low yield currency. For example, following a simple carry model, investors will be long the EUR/USD rate (i.e. long EUR and short USD) if the EUR interest rate is higher than the corresponding USD interest rate, and short the EUR/USD rate if the USD interest rate is higher.

The carry model generates trading signals solely depending on the corresponding interest rate differentials, which do not change very often. The downside of such a passive trading strategy is that it ignores all other current market information, which can possibly result in intolerable drawdowns. As a matter of fact, all major currency market players watch the market closely and trade actively. Therefore we propose a combined carry/MACD strategy where the MACD combinations retained function as confirmation filters to the carry

[35] As for chapter 2 (see footnote 13), the asset allocation set for the FX portfolio in this chapter remains unchanged for the entire data sample period.

model signals. We use the symbol $S_{n\,(t+1,t)}$ to denote the trading signals from a specific model at time t for time $t+1$, where the subscript n points to a given model: n takes the value of 1 for the benchmark MACD model, it takes the value of 2 for the carry model, and 3 for the combined carry/MACD model, so the trading strategy for a carry/MACD model is defined as[36]:

$$S_{3\,(t+1,t)} = \begin{cases} S_{2\,(t+1,t)} & S_{1\,(t+1,t)} * S_{2\,(t+1,t)} > 0 \\ 0 & S_{1\,(t+1,t)} * S_{2\,(t+1,t)} <= 0 \end{cases}$$

5.4.2 Conditional Market Volatility

Following chapter 2, we use the time-varying RiskMetrics volatility model to measure conditional market volatility and different trading decisions are adopted when a given level of conditional volatility has been breached. RiskMetrics is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \qquad (5.2)$$

where σ^2 is the volatility forecast of a specific asset, r^2 is the squared return of that asset, and $\mu = 0.94$ for daily data as computed in JP Morgan (1994)[37].

We find in chapter 2 and 3 that MACD models produce negative returns most of the time when the underlying market volatility is high. We study whether

[36] Note that the combined MACD signal S_1 is either long (+1) or short (-1), while the carry signal S_2 is either long (+1), short (-1) or square (0) in the case where both interest rates are equal.
[37] The assumption is that the mean of asset return r is zero so that $r^2_{(t)}$ represents the latest variance. In addition, at the beginning to initiate the computation, we set $\sigma^2_{(0)} = r^2_{(0)}$

the performance of the carry model is also affected by market volatilities. The entire sample period is split into 6 volatility regimes, ranging from periods with extremely low volatility to periods experiencing extremely high volatility[38]. The performance of the carry model for different volatility regimes is given in table 5.2 for the 9 currency markets under review, in terms of average daily returns.

Table 5.2 The average daily returns of the carry model in periods of different volatility regimes

* Full 6-year period 04/01/1999 to 31/05/2005

	Extremely Low Vol.	Medium Low Vol.	Lower Low Vol.	Lower High Vol.	Medium High Vol.	Extremely High Vol.
EUR/USD	0.015%	0.025%	0.038%	0.113%	0.007%	-0.101%
USD/JPY	0.030%	0.013%	0.002%	-0.010%	-0.040%	0.010%
GBP/USD	0.021%	0.073%	-0.005%	0.011%	0.029%	-0.042%
USD/CHF	-0.062%	0.003%	0.004%	0.010%	-0.038%	-0.003%
USD/CAD	0.012%	-0.009%	0.018%	0.044%	0.001%	-0.030%
AUD/USD	-0.032%	0.036%	0.037%	0.075%	-0.015%	-0.053%
EUR/GBP	0.060%	0.003%	0.022%	-0.021%	0.026%	-0.115%
EUR/JPY	0.056%	0.038%	-0.038%	0.028%	0.012%	-0.018%
EUR/CHF	0.025%	-0.012%	0.004%	0.002%	-0.021%	-0.005%

While the carry model performs reasonably well overall when FX markets are stable, it performs poorly, except for the USD/JPY, when underlying market volatility is extremely high. It also produces more negative returns for most of the markets when volatility is classified as "medium high" compared with

[38] Periods with different volatility levels are classified in the following way: we first calculate the rolling historical average volatility and its "volatility" (measured in terms of standard deviation σ), those periods with volatility forecasts between the average volatility (Avg. Vol.) and average plus one σ of the volatility (Avg. Vol + 1 σ) are classified as "Lower High Vol. Periods". Similarly, "Medium High Vol." (between Avg. Vol. + 1σ and Avg. Vol. + 2σ) and "Extremely High Vol." (above Avg. Vol. + 2σ) periods can be defined. Periods with low volatility are also defined following the same 1σ and 2σ approach, but with a minus sign.

more tranquil periods.

5.4.3 Volatility Filter Rules

As both the MACD and carry models behave differently in highly volatile markets, a different strategy needs to be adopted when the volatility regime changes. Again, we use the symbol $S_n^{(p)}{}_{(t+1,t)}$ to denote the trading signals from a specific model at time t for time $t+1$, where the superscript p is the volatility filter imposed on that particular model n: p takes the value of 0 if there is no volatility filter, it takes the value of 1 when the "no-trade" filter is used and 2 when a "reverse" filter is implemented.

5.4.3.1 "No-trade" Strategy

Since both the MACD and carry models tend to perform poorly in volatile markets, following chapter 2, the "no-trade" volatility filter rule proposed is to stay out of the market when the underlying volatility is forecast to be higher than a certain threshold T. A simple trading rule combined with a "no-trade" filter can be expressed as:

$$S_n^{(1)}{}_{(t+1,t)} = \begin{cases} S_n^{(0)}{}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ 0 & \sigma^2_{(t+1,t)} > T \end{cases}$$

5.4.3.2 *"Reverse" Strategy*

As in chapter 2, a "reverse" filter proposed is to reverse the signals generated when market volatility is forecast to be higher than a chosen threshold:

$$S_n{}^{(2)}{}_{(t+1,t)} = \begin{cases} S_n{}^{(0)}{}_{(t+1,t)} & \sigma^2{}_{(t+1,t)} < T \\ -(S_n{}^{(0)}{}_{(t+1,t)}) & \sigma^2{}_{(t+1,t)} > T \end{cases}$$

5.5 Empirical Results

Both the benchmark MACD and the combined carry/MACD models generate more trading signals than the passive carry model, so a performance comparison can reach biased results without taking account of the transaction costs incurred. In this study, we follow Lequeux and Acar (1998) to set the transaction cost as 0.03% per round-trip transaction for all exchange rates in the portfolio. Traditional performance measures after the deduction of transaction costs are shown in table 5.3. It should be noted that in this chapter, all currency returns are exclusive of interest rate gains generated by holding a specific currency: including such interest rates gains could further enhance the models performance displayed in table 5.3. Such effects can be more significant in the case of a simple carry model, which always holds a high yield currency. For instance, trading EUR/USD with the simple carry model, the annualised return for the whole 6-year period is 14.78% inclusive of interest rate gains compared to 10.88% exclusive of those gains. The risk-adjusted information ratio is 1.49 for the former

Table 5.3 Performance statistics

	6-Year	*4-Year*	*2-Year*	*6-Year*	*4-Year*	*2-Year*	*6-Year*	*4-Year*	*2-Year*
	04/01/99 31/03/05	02/01/01 31/03/05	02/01/03 31/03/05	04/01/99 31/03/05	02/01/01 31/03/05	02/01/03 31/03/05	04/01/99 31/03/05	02/01/01 31/03/05	02/01/03 31/03/05
Strategy #1	*Benchmark MACD Model*								
	Without Filter			**No-trade Filter**			**Reverse Filter**		
Annualised Net Return	0.36%	-1.07%	-1.06%	1.81%	1.15%	0.62%	3.04%	3.16%	2.04%
Annualised Net Volatility	5.41%	5.37%	5.50%	4.68%	4.62%	4.65%	4.85%	4.75%	4.82%
Net Information Ratio	0.07	-0.20	-0.19	0.39	0.25	0.13	0.63	0.66	0.42
Maximum Drawdown	-14.20%	-14.20%	-14.20%	-10.62%	-10.62%	-10.62%	-9.50%	-9.50%	-9.50%
Strategy #2	*Carry Model*								
	Without Filter			**No-trade Filter**			**Reverse Filter**		
Annualised Net Return	5.03%	5.40%	5.02%	5.86%	6.34%	6.42%	6.70%	7.27%	7.82%
Annualised Net Volatility	4.83%	4.35%	4.53%	4.28%	3.93%	3.97%	4.70%	4.44%	4.55%
Net Information Ratio	1.04	1.24	1.11	1.37	1.61	1.62	1.43	1.64	1.72
Maximum Drawdown	-7.26%	-5.05%	-5.05%	-6.37%	-4.22%	-4.22%	-5.51%	-3.81%	-3.81%
Strategy #3	*Combined Carry/MACD Model*								
	Without Filter			**No-trade Filter**			**Reverse Filter**		
Annualised Net Return	3.39%	2.45%	2.22%	4.07%	3.76%	3.06%	5.63%	5.92%	5.39%
Annualised Net Volatility	4.28%	4.00%	4.09%	3.65%	3.41%	3.43%	3.98%	3.74%	3.70%
Net Information Ratio	0.79	0.61	0.54	1.12	1.10	0.89	1.41	1.58	1.46
Maximum Drawdown	-7.45%	-7.45%	-7.45%	-4.28%	-4.28%	-4.28%	-3.87%	-3.71%	-3.71%

compared with 1.09 for the latter.

For the 3 periods and the 3 basic trading strategies considered, the simple carry model performs much better than the averaged performance of currency fund managers replicated by the benchmark MACD models. Compared to the MACD benchmark, the carry model not only generates higher returns, but also it reduces the investment risk with lower trading volatility and maximum drawdowns. As expected, the combined carry/MACD model, by generating more active trading signals further reduces investment volatility consistently across the different periods. Overall the carry model significantly outperforms the other two models in terms of annualised return and risk-adjusted information ratio.

For each trading strategy, the addition of the two volatility filters further enhances the performance of the three models. As far as the two filters are concerned, the "reverse" filter strategy performs better than the "no-trade" filter strategy in terms of annualised return, information ratio and maximum drawdown, while, not surprisingly, the "no-trade" filter strategy prevails in terms of trading volatility. It is hard to select a real "winning" volatility filter: on the one hand, the "no-trade" strategy enables investors to free funds out of a volatile FX market into other less turbulent financial markets which might further increase overall returns and reduce risk; on the other hand, the "reverse" filter strategy delivers higher returns that can only be met by the "no-trade" strategy in FX markets by the application of leverage with the associated higher transaction costs. It is therefore up to investors to choose the right strategy based on their risk tolerance and investment universe in terms of asset classes. But it is obvious that markets behave differently at high volatility levels and adaptive strategies like the ones suggested here should be adopted during those periods.

What is more, the risk-adjusted information ratios obtained from strategies using the filters proposed are also high in absolute terms, which suggests that the performance results obtained with the volatility filters are not only good when compared to the FX portfolio without filters, they are also attractive as such and actionable in a trading environment.

5.6 Concluding Remarks

The first motivation for this chapter was to study whether a simple passive carry model can outperform typical currency fund managers as replicated by dynamic MACD models following Lequeux and Acar (1998). Our results show that, for the 3 periods considered and for the 9 most heavily traded exchange rates, the simple carry model performs significantly better than the benchmark MACD model in terms of annualised return, annualised volatility, information ratio and maximum drawdown. Our empirical findings confirm previous results from the literature (such as, for instance, Frankel 1980, Bilson 1981, Taylor 1995 and Wolff 2000) that reject the simple risk-neutral efficient market hypothesis that the forward premium/discount is an optimal predictor of future exchange rate appreciation/depreciation.

Our results also show that a carry model performs poorly when market volatility is high and the model performance is significantly enhanced with the addition of volatility filters either to close market positions in volatile periods (with a "no-trade" filter), or to reverse the original trading signals if market volatility is higher than a given threshold (with a "reverse" filter).

While it is difficult to distinguish which volatility filter is superior to the other, the information ratios obtained from trading strategies using either filter are high, suggesting that such strategies are indeed attractive and actionable in a trading environment.

CHAPTER 6

Advanced Frequency and Time Domain Filters for Currency Portfolio Management

Chapter Overview

The first motivation for this chapter is to study the existence of cyclical properties in foreign exchange (FX) markets with the use of spectral analysis. Previous chapters show that volatility filters add value to alternative trading model performance in FX markets. We then study whether the performance of the spectral model will also be affected by alternative market volatility regimes.

Secondly, we study the economic value of a trading model based on spectral analysis compared with technical trending models replicating the performance of typical currency managers as in Lequeux and Acar (1998).

We find that both spectral models and moving average convergence divergence (MACD) technical trending models fail to perform satisfactorily when markets display cyclical properties. There is no evidence that the performance of this model is affected by volatility regime changes. Yet, a trading strategy combining volatility and spectral filters significantly improves the performance of traditional technical trading models for active currency portfolio management.

6.1 Introduction

Most of fund managers in the foreign exchange (FX) markets are technical traders, who mostly follow technical trending systems as evidenced by the high correlation of their performance with a portfolio of such systems (e.g. Lequeux and Acar, 1998). Billingsley and Chance (1996) mention that 70% of the Commodity Trading Advisors (CTAs) are trend followers and tend to trade in a similar manner. But markets are not always moving in trends which are just one of the basic elements of price movement, the other being range trading situations or cycles. As a matter of fact, Hurst (1997) notes that 23% of all price motion is oscillatory in nature. If this assumption is true, there is no reason to trade solely on the basis of technical trending rules at all times even when the underlying markets display strong cyclical properties.

The motivation for this chapter is twofold. Firstly, we study the existence of cyclical properties in FX markets. Specifically, we investigate the use of spectral decomposition with periodogram analysis to identify the cyclical properties of FX time series. Previous chapters show that volatility filters add value to alternative trading model performance in FX markets. We then study whether the performance of the spectral model will also be affected by alternative market volatility regimes.

Secondly, we study the economic value of a trading model based on spectral analysis. Once the underlying markets are found to be in cyclical mode, we compare the performance of the model utilizing spectral properties with the performance of technical trending models replicating the performance of FX fund managers, as in Lequeux and Acar (1998). As neither model provides satisfactory results, we then propose alternative trading strategies for when the markets studied are in cyclical mode.

The rest of the chapter is organized as follows: section 6.2 describes the data used and the FX portfolio formed, section 6.3 explains the methodology of spectral decomposition with the use of periodogram analysis. The following 2 sections illustrate the two filters proposed: namely volatility filters that are imposed on the trend-following models in section 6.4 and spectral filters proposed for trading in periods when markets are in cyclical mode in section 6.5. Section 6.6 presents the empirical results, focusing on the models performance during different sample periods, followed by concluding remarks in section 6.7.

6.2 Data and FX Portfolio

The entire sample covers the period from 04/01/1999 to 31/05/2005 with 1663 days of observations and all datasets used are daily closing prices in London obtained from Datastream. To measure the consistency of the performance measures, we split the entire sample period into 3 periods as: the full 6-year period (04/01/1999 - 31/05/2005), the last 4-year period (02/01/2001 - 31/05/2005) and the last 2-year period (02/01/2003 - 31/05/2005).

The daily currency returns *r* for time period *t* are calculated as the percentage change of the daily currency rate p:

$$r_t = (\frac{p_t - p_{t-1}}{p_{t-1}}) \tag{6.1}$$

Lequeux and Acar (1998) introduce a dynamic currency index (AFX index) to replicate the performance of typical currency fund managers. The index consists of 7 currency futures using 3 simple MACD (namely 1 and 32-day, 1 and 61-day and 1 and 117-day) strategies with each MACD taking the same weight in generating trading signals. They find that the AFX index has a high correlation with and low tracking error to currency managers performance. Following the same MACD combination strategy (henceforth the MACD model), we form the FX portfolio using currency spot rates since trading volumes in the FX spot market are much higher than those in the futures market[39]. We also expand the portfolio composition to include the 9 most heavily traded major exchange rates according to the recent BIS FX trading survey[40] (they represent over 78% of the USD 1.8 trillion daily FX turnover reported for April 2004) and update the portfolio-weighting scheme using the data from this survey (BIS 2004). Both the asset combination and weights of the FX portfolio are shown in table 6.1 below[41].

---

[39] The use of these preset parameters implies that we do not need a calibration period for in-sample model optimization and consequently all performance computations are out-of-sample.

[40] We use the notation of the International Organization for Standardization (IOS) for all the exchange rates considered.

[41] As for chapter 2 (see footnote 13), the asset allocation set for the FX portfolio in this chapter remains unchanged for the entire data sample period.

Table 6.1 ***FX portfolio currency allocation***

Currency	EUR /USD	USD /JPY	GBP /USD	USD /CHF	USD /CAD	AUD /USD	EUR /GBP	EUR /JPY	EUR /CHF
Weights	35.76%	21.13%	17.49%	5.57%	5.07%	6.42%	3.07%	3.64%	1.85%

6.3 Spectral Analysis: the Methodology

In this study, we use spectral analysis to measure market cycles. Compared to alternative methods measuring market cycles, spectral analysis is the only way to obtain a high resolution cycle measurement using only a short amount of data (Ehlers, 1999). Spectral decomposition analysis is carried out using periodogram analysis (see, amongst others, Chatfield 1994 and Judge *et al.* 1985). The spectral periodogram analysis is able to extract from a time series its spectral properties which include the maximum amplitude, its corresponding cycle length and phase angles of the observations. Specifically, the periodogram decomposition searches the largest amplitude and assumes that this amplitude dominates over the other amplitudes. This amplitude and its associated frequency are then used to estimate the original time series. The phase angle of each observation can then be estimated. For example, a time series X_t can be represented by a finite Fourier series as:

$$X_t = a_0 + \sum_{p=1}^{(N/2)-1} \left[a_p \cos(2\pi pt/N) + b_p \sin(2\pi pt/N)\right] + a_{pN/2} \cos(\pi t) \quad (6.2)$$

and coefficients in equation (6.2) are defined as:

$$a_0 = \bar{x} \tag{6.3}$$

$$a_{N/2} = \sum_{t=1}^{N} (-1)^t x_t / N \tag{6.4}$$

$$a_p = \frac{2}{N} \sum_{t=1}^{N} \left[x_p \cos(2\pi pt / N) \right] \tag{6.5}$$

$$b_p = \frac{2}{N} \sum_{t=1}^{N} \left[x_p \sin(2\pi pt / N) \right] \text{ with } p=1,\ldots,(N/2)-1, \tag{6.6}$$

The amplitude R_p and phase Φ_p of the pth harmonic is then given by:

$$R_p = \sqrt{a_p^2 + b_p^2} \tag{6.7}$$

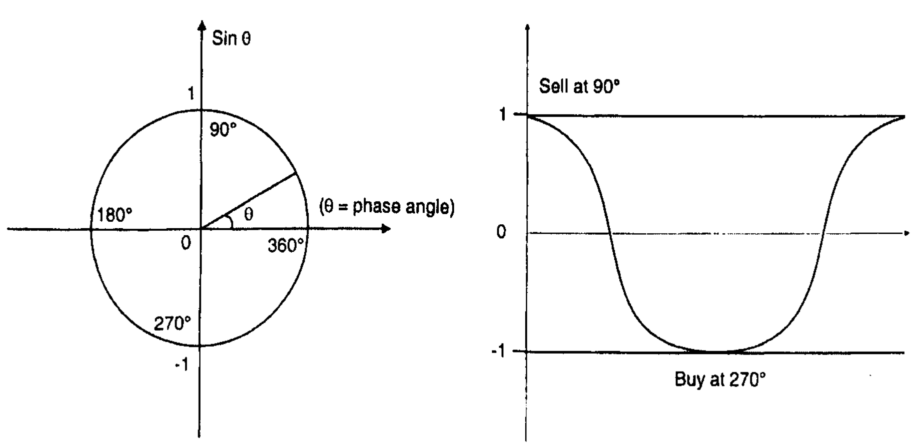
$$\phi_p = \tan^{-1}\left(-b_p / a_p\right) \tag{6.8}$$

The assumption is that the harmonic of the maximum amplitude p_{max} is sufficient to estimate the series, i.e.

$$X_t = a_0 + a_{p\max} \cos(2\pi p_{\max} t / N) + b_{p\max} \sin(2\pi p_{\max} t / N) + a_{pN/2} \cos(\pi t) \tag{6.9}$$

First, the series X_t should be detrended, otherwise a noticeable trend in the data will be interpreted as the dominant cycle (Kaufman 1998). The presence of a deterministic trend is confirmed in all the 9 currency rates studied (see appendix A.34-A.42 for the test output tables). In this chapter we demean and detrend the series using a simple linear regression to remove any trend element within the series. As explained above, the spectral periodogram analysis can extract its spectral properties from a time series, including the maximum amplitude, its corresponding cycle length and phase angles of the observations. In this study, we apply a multiple window frame approach to best extract these spectral properties: three fixed rolling windows of 30, 60, 120 days are used, with the longer window a multiple of the shorter window[42]. Each window will have its own spectral properties so that, if at least two of these three windows exhibit the same cycle length and maximum amplitude, one can assume that the time series under review shows some general cyclicality. The resulting cycle length is then computed as above, while the resulting phase angle and amplitude are the average computation from the two windows.

Figure 6.1 Ranging markets and their trigonometric circle representation



With these spectral properties identified, it is now possible to derive corresponding trading strategies. An investment model based on spectral

[42] The selection of 30-, 60- and 120-day window size also corresponds roughly to the specifications of the MACD models retained (1D-32D, 1D-61D, 1D-117D). See also our comments in footnote 39 above.

decomposition (henceforth the spectral model) utilizes the spectral properties of the cycle lengths and phase angles identified. Having determined the dominant cycle over a given time window, the model extracts the phase angle across the cycle. Over an entire cycle length and starting from a median position (i.e. the middle of the trading range), the phase angle will move to 90°, the top of the cycle and of the trading range, upto 270°, the bottom of the cycle and of the trading range. This is illustrated in figure 6.1.

Table 6.2 Statistics and models performance for cyclical periods

* Full 6-year period 04/01/1999 to 31/05/2005

	Periods when Market in Cycle		Cumulative Return when Market in Cycle	
	# of Observations	**% Percentage**	**Spectral Model**	**MACD Models**
EUR/USD	464	27.90%	-1.65%	-7.51%
USD/JPY	612	36.80%	23.24%	-17.92%
GBP/USD	493	29.65%	-1.53%	-1.69%
USD/CHF	434	26.10%	-9.08%	-7.29%
USD/CAD	437	26.28%	-14.18%	1.58%
AUD/USD	482	28.98%	-1.39%	-5.56%
EUR/GBP	465	27.96%	9.65%	-18.02%
EUR/JPY	584	35.12%	0.01%	1.86%
EUR/CHF	380	22.85%	7.19%	-7.06%
Average	***483***	***29.07%***	***1.36%***	***-6.85%***

The chosen trading strategy is to go long the underlying asset if the resulting phase angle at the end point of the time series is moving from 270° to 90°, the upward part of the cycle, and to short the asset if the resulting phase angle is moving from 90° to 270°, the downward part of the cycle. We apply the spectral periodogram analysis and its associated trading strategy to the 9 exchange rates studied. Periods when markets are in cyclical mode and performance comparison between the spectral model and the MACD model during such time can be found in table 6.2.

Table 6.2 shows that FX markets display cyclical properties on average about 29% of the time. This is in line with Hurst (1997) statement that 23% of all price motion is oscillatory in nature. Besides, the MACD model performs so poorly that 7 out of the 9 markets considered generate negative returns when these markets are in cyclical mode. Although the spectral model performs better for 6 out of the 9 exchange rates under review with an average cumulative return of 1.36%, this performance, which is very much due to the excellent results for the USD/JPY, is not convincingly good with 5 of the 9 exchange rates being negative.

6.4 Conditional Volatility and Volatility Filter Rules

6.4.1 Conditional Market Volatility

Following chapter 2, we use the time-varying RiskMetrics volatility model to measure conditional market volatility. RiskMetrics is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \tag{6.10}$$

where σ^2 is the volatility forecast of a specific asset, r^2 is the squared return of that asset, and $\mu = 0.94$ for daily data as computed in JP Morgan (1994)[43].

Table 6.3 Spectral model average daily returns when in cyclical mode and in periods of different volatility regimes

* Full 6-year period 04/01/1999 to 31/05/2005

	Extremely Low Vol.	Medium Low Vol.	Lower Low Vol.	Lower High Vol.	Medium High Vol.	Extremely High Vol.
EUR/USD	0.06%	0.14%	-0.07%	-0.02%	-0.06%	0.02%
USD/JPY	0.03%	0.06%	0.03%	0.01%	0.10%	-0.03%
GBP/USD	-0.05%	-0.01%	-0.01%	0.06%	-0.07%	0.00%
USD/CHF	-0.10%	-0.01%	-0.02%	-0.06%	-0.02%	0.30%
USD/CAD	0.20%	0.00%	-0.06%	-0.06%	0.02%	-0.10%
AUD/USD	0.00%	-0.05%	-0.02%	0.00%	0.07%	0.07%
EUR/GBP	0.06%	-0.03%	0.02%	-0.08%	0.17%	0.14%
EUR/JPY	-0.13%	0.03%	0.03%	0.01%	-0.35%	0.12%
EUR/CHF	-0.04%	0.02%	0.02%	0.04%	-0.08%	0.04%

In chapter 2 and 3, we find that MACD models produce negative returns most of the time when the underlying market volatility is high. We study whether the performance of the spectral model will also be affected by alternative market volatility regimes. The entire sample period is split into 6 sub-periods, ranging from periods with extremely low volatility to periods experiencing extremely high volatility[44]. The performance of the spectral model in the 9 currency markets, in terms of average daily returns, for different volatility

[43] The assumption is that the mean of asset return r is zero so that $r^2_{(t)}$ represents the latest variance. In addition, at the beginning to initiate the computation, we set $\sigma^2_{(0)} = r^2_{(0)}$

[44] Periods with different volatility levels are classified in the following way: we first calculate the rolling historical average volatility and its "volatility" (measured in terms of standard deviation σ), those periods with volatility forecasts between the average volatility (Avg. Vol.) and average plus one σ of the volatility (Avg. Vol + 1 σ) are classified as "Lower High Vol. Periods". Similarly, Medium High Vol. (between Avg. Vol. + 1σ and Avg. Vol. + 2σ) and Extremely High Vol. (above Avg. Vol. + 2σ) periods can be defined. Periods with low volatility are also defined following the same 1σ and 2σ approach, but with a minus sign.

regimes can be found in table 6.3.

Generally, the spectral model performs poorly across the different volatility regimes, and there is no evidence that the performance of this model is affected by volatility regime changes.

6.4.2 Volatility Filter Rules

In pervious chapters we find that MACD models produce negative returns most of the time when the underlying market volatility is high. We then propose two volatility filters, namely a "no-trade" filter and a "reverse" filter to improve model performance. In this chapter, we apply the same volatility filters on the MACD model and use the symbol $MA^{(p)}{}_{(t+1,t)}$ to denote the trading signals from an MACD model at time t for time $t+1$, where the superscript p is the volatility filter imposed on that model: p takes the value of 0 if there is no volatility filter, it takes the value of 1 when the "no-trade" filter is used and 2 when a "reverse" filter is in use.

6.4.2.1 "No-trade" Volatility Filter Strategy

Since MACD models are found to perform poorly in volatile markets, following chapter 2, the "no-trade" volatility filter rule proposed is to stay out of the market when the underlying volatility is forecast to be higher than a certain threshold T. A simple trading rule combined with a "no-trade" volatility filter can be expressed as:

$$MA^{(1)}_{(t+1,t)} = \begin{cases} MA^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ 0 & \sigma^2_{(t+1,t)} > T \end{cases}$$

6.4.2.2 "Reverse" Volatility Filter Strategy

As in chapter 2, a "reverse" filter proposed is to reverse the signals generated when market volatility is forecast to be higher than a chosen threshold:

$$MA^{(2)}_{(t+1,t)} = \begin{cases} MA^{(0)}_{(t+1,t)} & \sigma^2_{(t+1,t)} < T \\ -\left(MA^{(0)}_{(t+1,t)} \right) & \sigma^2_{(t+1,t)} > T \end{cases}$$

6.5 Spectral Filter Rules

Since neither the spectral model nor the MACD model perform well when currency markets are in cyclical mode, different trading strategies should be adopted during such times. We propose to further impose a spectral filter q onto the above MACD signals ($MA^{(p)}_{(t+1,t)}$) which then generates the new trading signals marked as $MA^{(p,q)}_{(t+1,t)}$: q takes the value of 0 if there is no spectral filter, it takes the value of 1 when the "no-trade" spectral filter is used and 2 when a "reverse" spectral filter is in use.

6.5.1 "No-trade" Spectral Filter Strategy

Since both the spectral and MACD models are found to perform poorly when markets are in cyclical mode, the first spectral filter rule proposed is to stay out of the market when the underlying market is found to be cyclical. This spectral filter can be combined with any of the volatility filters explained above. For instance, a model with a "no-trade" volatility filter combined with a "no-trade" spectral filter can be expressed as:

$$MA^{(1,1)}_{(t+1,t)} = \begin{cases} 0 & \textit{Market in Cycle} \\ MA^{(1,0)}_{(t+1,t)} & \textit{Else} \end{cases}$$

where $MA^{(1,0)}_{(t+1,t)}$ is the same as $MA^{(1)}_{(t+1,t)}$ in section 6.4.2.1.

6.5.2 "Reverse" Spectral Filter Strategy

We saw in section 6.4 that MACD models generate significant negative returns for most exchange rates when they are in a cyclical mode. We therefore propose to reverse the signals from the MACD models when markets are cyclical and a model with a "reverse" volatility filter combined with a "reverse" spectral filter can be expressed as:

$$MA^{(2,2)}_{(t+1,t)} = \begin{cases} -\left(MA^{(0,0)}_{(t+1,t)} \right) & \textit{Market in Cycle} \\ MA^{(2,0)}_{(t+1,t)} & \textit{Else} \end{cases}$$

where $MA^{(2,0)}_{(t+1,t)}$ is the same as $MA^{(2)}_{(t+1,t)}$ and $MA^{(0,0)}_{(t+1,t)}$ is the same as $MA^{(0)}_{(t+1,t)}$ in section 6.4.2.2.

6.6 Empirical Results

In this study, we follow Lequeux and Acar (1998) to set the transaction cost as 0.03% per round-trip transaction for all exchange rates in the portfolio. Transaction costs and performance measures after deduction of these costs are shown in table 6.4 (note that these results do not include interest income or payments for holding a given currency).

In all scenarios, after accounting for transaction costs, the addition of the two spectral filters significantly improves the performance of the MACD models replicating typical currency managers, both with and without volatility filters. As far as the two spectral filters are concerned, the "reverse" filter strategy performs better than the "no-trade" filter strategy in terms of annualized return, and, as could be expected, the "no-trade" filter strategy prevails in terms of trading volatility. Although the "reverse" filter produces significantly higher risk-adjusted information ratio than the "no-trade" filter, in the latter case the investments are out of the market for considerably long periods (29% of the time on average for the data period considered), during which investors are able to free funds and invest into other less turbulent markets or adopt alternative profitable FX trading strategies which might further increase yield and reduce risk[45]. In addition, the "reverse" filter strategy delivers higher returns that can only be met by the "no-trade" strategy in FX markets by the application of leverage with the associated higher transaction costs. Accordingly, there is no real "winning" spectral filter and it is up to investors to

---

[45] For instance, when the market is in cyclical mode, investors can select to use a carry model which is shown to be profitable in FX markets (see chapter 5 or Dunis and Miao 2006).

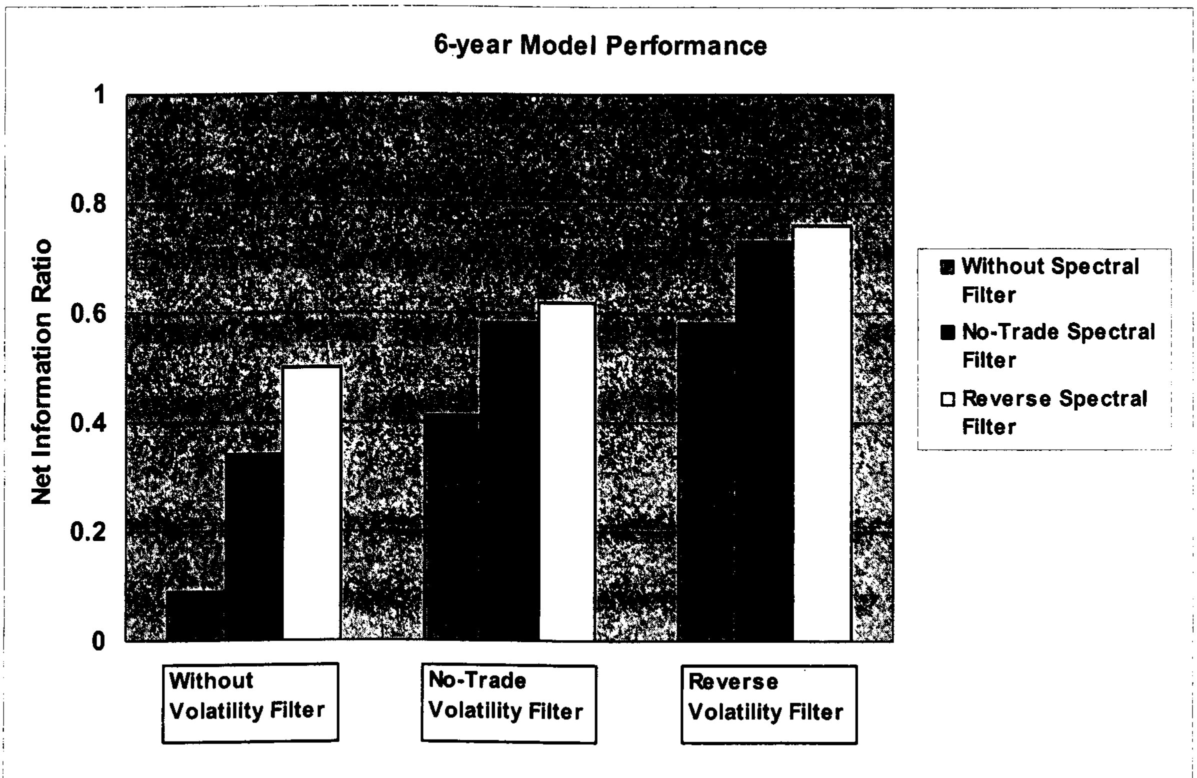
Table 6.4 Performance statistics

	6-Year	4-Year	2-Year	6-Year	4-Year	2-Year	6-Year	4-Year	2-Year
	04/01/99 31/05/05	02/01/01 31/05/05	02/01/03 31/05/05	04/01/99 31/05/05	02/01/01 31/05/05	02/01/03 31/05/05	04/01/99 31/05/05	02/01/01 31/05/05	02/01/03 31/05/05
Strategy #1	*MACD model without volatility filter*								
	Without Spectral Filter			**No-Trade Spectral Filter**			**Reverse Spectral Filter**		
Annualised Net Return	0.50%	-0.43%	-1.06%	1.74%	0.38%	-0.04%	2.59%	0.83%	0.55%
Annualised Net Volatility	5.41%	5.35%	5.39%	4.29%	4.39%	4.24%	4.50%	4.50%	4.33%
Net Information Ratio	0.09	-0.08	-0.20	0.41	0.09	-0.01	0.58	0.19	0.13
Maximum Drawdown	-14.20%	-14.20%	-14.20%	-7.56%	-7.56%	-7.33%	-8.23%	-8.23%	-5.54%
Transaction Costs	3.71%	2.69%	1.49%	3.62%	2.68%	1.44%	6.06%	4.30%	2.47%
Strategy #2	*MACD with No-trade volatility filter*								
	Without Spectral Filter			**No-Trade Spectral Filter**			**Reverse Spectral Filter**		
Annualised Net Return	1.57%	1.10%	0.25%	2.18%	1.34%	0.68%	3.03%	1.79%	1.27%
Annualised Net Volatility	4.67%	4.61%	4.59%	3.78%	3.85%	3.72%	4.13%	4.07%	3.96%
Net Information Ratio	0.34	0.24	0.06	0.58	0.35	0.18	0.73	0.44	0.32
Maximum Drawdown	-10.67%	-10.67%	-10.67%	-5.56%	-5.56%	-5.56%	-6.30%	-6.30%	-5.03%
Transaction Costs	3.92%	2.76%	1.45%	3.61%	2.65%	1.35%	6.07%	4.28%	2.38%
Strategy #3	*MACD with Reverse volatility filter*								
	Without Spectral Filter			**No-Trade Spectral Filter**			**Reverse Spectral Filter**		
Annualised Net Return	2.44%	2.43%	1.32%	2.42%	2.11%	1.17%	3.34%	2.62%	1.84%
Annualised Net Volatility	4.85%	4.78%	4.75%	3.93%	4.01%	3.90%	4.37%	4.31%	4.25%
Net Information Ratio	0.50	0.51	0.28	0.62	0.53	0.30	0.76	0.61	0.43
Maximum Drawdown	-9.58%	-9.58%	-9.58%	-5.99%	-5.99%	-5.99%	-6.22%	-6.22%	-4.55%
Transaction Costs	5.46%	3.74%	2.03%	4.87%	3.48%	1.83%	6.87%	4.84%	2.65%

choose the right strategy based on their risk tolerance. But it is obvious that markets behave differently when FX markets are in cyclical mode and adaptive strategies like the ones suggested should be adopted during those periods.

Figure 6.2 Model performance comparison in terms of net information ratio

* Full 6-year period 04/01/1999 to 31/05/2005



Finally, our results show that volatility filters improve the performance of trend-following MACD models, which confirms the results from previous chapters. They also demonstrate, as evidenced in figure 6.2 on net information ratios which is a good summary of our findings, that volatility filters combined with spectral filters further improve the performance of such technical trading models.

6.7 Concluding Remarks

In this chapter, we set out to investigate the existence of cyclical properties in FX markets and the use of spectral decomposition to identify the cyclical properties of FX time series. We then studied whether the performance of the spectral model would also be affected by alternative market volatility regimes. Generally, the spectral model performs poorly across the different volatility regimes, and there is no evidence that the performance of this model is affected by volatility regime changes.

We further analysed the economic value of trading models based on spectral analysis, comparing the performance, once underlying markets are found to be in cyclical mode, of models using spectral properties with the performance of traditional technical trending models replicating the performance of FX fund managers, as in Lequeux and Acar (1998).

As neither model provides satisfactory results, we then proposed alternative trading strategies based on a combination of frequency and time domain filters for when the markets studied are in cyclical mode. The strategies proposed show that, for the exchange rates and the period concerned, this combination of volatility and spectral filters significantly improves the performance of traditional technical trading models for active currency portfolio management.

PART THREE

Volatility Filters for Dynamic Portfolio Optimisation

CHAPTER 7

Volatility Filters for Dynamic Portfolio Optimisation

Chapter Overview

It is well known that volatilities and correlations of international stock markets tend to increase in times of financial instability. In this chapter, we extend volatility filters to asset allocation and propose a dynamic portfolio rebalancing scheme where the underlying market volatility functions as a timing device for portfolio reallocation and portfolio is only rebalanced when the underlying volatility regime changes.

In addition, the traditional Markowitz mean variance (MV) optimisation can lead to an "inefficient frontier" with wrong expected returns. We propose a risk-adjusted expected return (RAER) approach where expected returns are expressed as a linear function of the risk incurred through a risk-aversion coefficient.

Our results show that the addition of volatility filters adds value to the portfolio performance in all the periods considered. Moreover, the proposed RAER approach produces most consistent performance with and without the constraint on short-selling compared to other dynamic rebalancing approaches and a constant equally weighted portfolio.

7.1 Introduction

An accurate estimation of the covariance matrix is a key input to traditional Markowitz (1952) mean-variance (MV) portfolio optimisation. Apart from early works where variance and covariance were assumed to be constant over time, more recent studies show that variance and covariance are actually time-varying and can be forecast, to some extent, accurately. Numerous approaches have been introduced to model the so-called conditional variance and covariance, and development in information technology makes most of these techniques easy to implement. The success of these quantitative models therefore provides an opportunity for optimising portfolios dynamically with an updated forecast of the covariance matrix. The question is whether a dynamic rebalancing scheme accounting for the variability of the covariance matrix can outperform a portfolio with constant weights after transaction costs are deducted.

One important feature of time-varying variances and covariances among international stock markets has been well documented in the literature (e.g. Erb *et al.* 1994 and Solnik *et al.* 1996): the so-called contagion where correlations between global stock markets tend to increase in times of financial instability. Besides, bonds can offer effective diversification in time of instability since its correlation with stocks temporarily changes to negative during such times. The traditional MV optimisation ignoring international contagion thus tends to underweight bonds at times of financial instability and overweight them at other times.

While it is generally accepted that volatility can be forecast to some degree, there is still a controversy over whether asset returns are forecastable. The optimal portfolio asset weights are so sensitive to the expected return that portfolio optimisation using inaccurate expected return can result in poor portfolio performance. Michaud (1989) states that MV optimised portfolios are "estimation error maximisers", since the MV optimisation significantly overweights securities with high estimated returns and underweights those with low estimated returns.

The motivation for this chapter is twofold. Firstly, dynamic portfolio rebalancing using conditional covariance involves a frequent modification of asset weights, thus the benefits from dynamic rebalancing can be quickly erased by transaction costs. Furthermore, the existence of international contagion suggests a covariance matrix regime change between "normal", i.e. quiet times and times of financial instability. We propose a dynamic rebalancing scheme where the underlying market volatility functions as a timing device for portfolio reallocation and the portfolio is only rebalanced when the underlying volatility regime changes.

Secondly, MV optimisation is very sensitive to the covariance matrix and return input assumptions. Contrary to expected returns, conditional variance and covariance can be estimated accurately to some extent. Therefore using the dynamic forecast of the covariance matrix as one of the inputs, we propose a risk-adjusted expected return (RAER) approach where expected returns are expressed as a linear function of the risk incurred through a risk-aversion coefficient. This risk-aversion coefficient is set as time-varying and follows an AR(1) process. The proposed RAER approach is benchmarked against other commonly used dynamic approaches as well as a constant equally weighted portfolio.

Our results show that the addition of a volatility filter onto the dynamic portfolio rebalancing scheme adds significant value to portfolio performance in terms of annualised return, maximum drawdown and risk-adjusted information ratio over the entire review period and all the 3 sub-periods. Moreover, the proposed RAER approach produces a more consistent performance with and without the constraint on short-selling compared to other dynamic rebalancing approaches and a constant equally weighted portfolio.

The rest of the chapter is organized as follows: section 7.2 presents a brief review of the relevant literature, section 7.3 describes the data and section 7.4 explains the methodology. Section 7.5 presents the empirical results, focusing on the portfolio performance during different sub-periods, followed by concluding remarks in section 7.6.

7.2 Literature Review

International equity market correlation has been widely studied. Previous studies[46] conclude that international correlations are much higher in periods of volatile markets. Traditional MV portfolio optimisation technique using the

[46] See, for instance, Erb *et al.* (1994), Solnik *et al.* (1996), Ramchmand and Susmel (1998) and Longin and Solnik (2001).

full covariance matrix thus fails to work during periods of financial instability when volatility and correlations tend to increase. Among others, Michaud (1989) states that the estimation risk increases even more in times of financial instability when both volatilities and correlations tend to temporarily shift away from their long-run averages.

The increase of volatilities and correlations among stocks markets in volatile markets reduces the benefits of portfolio diversification when they are most needed. Nevertheless, Gulko (2002) states that the positive correlation between the returns of U.S. stocks and Treasury bonds temporarily changes to negative during times of financial instability, which means that U.S. Treasury bonds offer effective diversification during such times. The presence of regimes with different volatilities and correlations provides an opportunity for portfolio optimisation using regime-switching models deriving from the seminal work of Hamilton (1989) to allow data to be drawn from two or more regimes. Chow *et al.* (1999) show that there is a significant difference in terms of optimal weights between the MV model using the full covariance matrix and one that distinguishes volatility regimes. But they do not provide the performance and risk of their portfolio. Using the approach of Chow *et al.* (1999), Bauer *et al.* (2004) form a global portfolio and find that, after accounting for transaction costs, the benefits from portfolio optimisation using regime-switching disappear.

7.3 Data

The global portfolio studied in this chapter takes the perspective of a U.S investor with component assets drawn from stock, bond and commodity markets. The five assets retained are MSCI USA, MSCI Europe, MSCI Japan, Lehman Brother U.S. Aggregate Bonds (LEHM Bond) and Goldman Saches Commodity Index (GSCI). The two foreign stock assets (MSCI Europe and MSCI Japan) are also dollar denominated, implying that the portfolio is immune from foreign exchange risk.

The weekly data used in this study are Wednesday closing prices. When Wednesday is a holiday, we use the closing price of the preceding working day. The weekly asset returns *r* at time period *t* are calculated as the percentage change of the weekly price *p*:

$$r_t = \left(\frac{p_t - p_{t-1}}{p_{t-1}}\right) \tag{7.1}$$

The entire sample period is from 02/01/1989 to 29/12/2004 with 835 weeks of observations and all datasets used are obtained from Datastream. We use data of the first three years, from 02/01/1989 to 25/12/1991 with 156 weeks of observations, for in-sample purpose. More specifically, data for this period are used for conditional variance and covariance initialisation and volatility filter threshold optimisation. The rest of the datasets, from 01/01/1992 to 29/12/2004 with 679 weeks of observations, are for out-of-sample performance evaluation. To measure the consistency of portfolio performance, the entire review period is further split into 3 sub-periods of equal length.

Full Review Period: 01/01/1992 to 29/12/2004 (679 observations)

Performance Sub-Period 1: 01/01/1992 to 24/04/1996 (226 observations)

Performance Sub-Period 2: 01/05/1996 to 23/08/2000 (226 observations)

Performance Sub-Period 3: 30/08/2000 to 29/12/2004 (227 observations)

7.4 Dynamic Portfolio Rebalancing and Filter Rule: the Methodology

7.4.1 Expected Variance and Covariance

An accurate estimation of the covariance matrix is an important input to the MV optimisation process. In this chapter we use two approaches to compute the conditional variance and covariance of the underlying assets: the RiskMetrics approach and the rollover historical covariance matrix approach. Jobson and Korkie (1981) use Monte Carlo simulations to estimate expected returns and find that the average of the simulated optimal portfolios significantly underperforms an equally weighted portfolio. All dynamic optimised portfolios are then assessed not only in terms of performance measures but also compared to the performance of an equally weighted portfolio.

7.4.1.1 RiskMetrics Approach

The time-varying RiskMetrics variance and covariance model was developed by JP Morgan (1994) for the measurement, management and control of market risks in its trading, arbitrage and own investment account activities. The RiskMetrics conditional variance model can be seen as a special case of

Bollerslev (1986) GARCH model with pre-determined decay parameters, and it is calculated using the following formula:

$$\sigma^2_{(t+1/t)} = \mu * \sigma^2_{(t/t-1)} + (1-\mu) * r^2_{(t)} \tag{7.2}$$

where σ^2 is the variance forecast of a specific asset, r^2 is the squared return of that asset, and μ = 0.96 for weekly data as computed in JP Morgan (1994).

Similarly, the RiskMetrics conditional covariance model is calculated using the following formula:

$$\sigma^2_{1,2\ (t+1/t)} = \mu * \sigma^2_{1,2\ (t/t-1)} + (1-\mu) * r_{1(t)} * r_{2(t)} \tag{7.3}$$

where $\sigma^2_{1,2}$ is the conditional covariance between asset 1 and asset 2, r_1 and r_2 are the returns of the two assets, and μ = 0.96 for weekly data.

7.4.1.2 Rollover Historical Covariance Matrix Approach

It is popular among market practitioners to use historical unconditional covariance as a forecast for the future. From a dynamic perspective, this involves the use of rollover approach where the rolling one step ahead forecast is the mean over a certain period (rolling window). The problem with such an approach is the choice of the rolling window, with the appearance of the so call "ghost features" (see Bentz 2003). The other problem with these measures is that they are unconditional with no sense of market timing. In this study, we set the rolling window size at 12 weeks so that the 1-week out-of-sample forecast roughly represents 10% of the estimation period.

7.4.2 Expected Returns

Best and Grauer (1991) show that the main source of randomness in the MV efficient zone is related to the expected return component. Expected returns are difficult to estimate, and two approaches were previously proposed in the context of MV optimisation. The historical average approach assumes that the expected return equals its historical average over a given period. The problem is that historical average is a very poor estimate of future returns and portfolio optimisation can further maximise estimation error as mentioned by Michaud (1989). In view of the difficulty of estimating expected returns one can implement, the minimum variance approach assuming that expected returns for all the underlying assets are the same so that one optimises the portfolio by minimising the portfolio variance utilising only the estimated covariance matrix regardless of the expected returns. Since the expected returns for low risk assets like bonds are significantly lower than expected returns for high risk assets like stocks, this minimum variance approach will tend to overweight low risk assets and underweight high risk assets.

We propose a risk-adjusted expected return (RAER) approach which assumes that the expected return over one asset is highly correlated to that asset's expected volatility: if the volatility estimate is high for one asset, investors should also expect a high return. Investors will accept a low return only if the associated risk is low as well. Under such assumption, expected returns are expressed as a linear function of the risk incurred through a risk-aversion coefficient. This risk-aversion coefficient is not constant over time since investors' expectations are adaptive: if the risk-adjusted return is low over the most recent period, investors will expect a low risk-adjusted return in the future and vice versa. Therefore the multiplier is assumed to be time-varying and it follows an AR(1) process as:

$$r_{(t+1/t)} = \beta_{(t+1/t)} * \sigma_{(t+1/t)}$$
$$\beta_{(t+1/t)} = \mu * \beta_{(t/t-1)} + (1-\mu) * \beta_{(t)} \tag{7.4}$$

where the multiplier β is the expected trade-off between return and risk. Specifically, $\beta_{(t+1,/t)}$ is the one step ahead forecast of β, while $\beta_{(t)}$ is the realised β at time t, which is the underlying asset return $r_{(t)}$ divided by the corresponding volatility. This trade off multiplier β follows an AR(1) process with the decay factor μ = 0.96 for weekly data. Equation (7.4) can also be seen as a special case of a GARCH(1,1)-M equation with time-varying parameters.

7.4.3 International Contagion

It is well known that there is contagion among international stock markets, and the volatilities and correlations tend to increase in times of financial instability. On the other hand, bonds can offer effective diversification in times of instability since its correlation with stocks temporarily changes to negative during such times. The traditional MV optimisation ignoring international contagion thus tends to underweight bonds in times of financial instability and overweight them at other times. The effects of contagion are exhibited in table 7.1 where covariance matrices for different volatility regimes are displayed. Since the portfolio is established from an U.S. investor's perspective, we arbitrarily set the volatility forecast of MSCI USA as an

Table 7.1 ***Correlation matrix for different volatility regimes***

* The underlying market volatilities are placed on top of the correlation matrix to illustrate the change of volatility regimes.

Full Review Period Correlation/Volatility Matrix

	MSCI USA	MSCI EUROPE	MSCI JAPAN	LEHM BOND	GSCI
Volatility	16.03%	16.65%	23.03%	3.93%	17.10%
MSCI USA	1				
MSCI EUROPE	0.618	1			
MSCI JAPAN	0.267	0.357	1		
LEHM BOND	0.156	0.129	-0.012	1	
GSCI	0.027	0.020	0.053	-0.059	1

Correlation/Volatility Matrix in times of financial instability

	MSCI USA	MSCI EUROPE	MSCI JAPAN	LEHM BOND	GSCI
Volatility	20.70%	21.16%	24.68%	3.83%	19.98%
MSCI USA	1				
MSCI EUROPE	0.701	1			
MSCI JAPAN	0.342	0.370	1		
LEHM BOND	-0.130	-0.109	-0.062	1	
GSCI	0.023	-0.001	0.050	-0.095	1

Correlation/Volatility Matrix during "normal times"

	MSCI USA	MSCI EUROPE	MSCI JAPAN	LEHM BOND	GSCI
Volatility	12.05%	12.89%	21.89%	3.99%	14.93%
MSCI USA	1				
MSCI EUROPE	0.565	1			
MSCI JAPAN	0.218	0.348	1		
LEHM BOND	0.342	0.284	0.020	1	
GSCI	0.029	0.034	0.055	-0.035	1

indicator to classify different regimes and periods when volatility forecasts are higher than a certain threshold are classified as times of financial instability with the remaining periods considered as "normal" times[47].

The effect of contagion can be well observed from table 7.1, volatilities and correlations between the stocks increase significantly in times of financial instability compared to those in normal times. On the other hand, LEHM bond and GSCI commodity's correlations to the stocks decrease significantly during volatile periods, which suggests that both bond and commodities can offer effective diversification during these periods. Such benefits are more obvious in the case of bonds where all correlations between LEHM bond and stocks change from positive in normal times to negative during instability. The full covariance matrix, ignoring the effects of volatility regimes on the variability of correlations, thus underestimates correlations between stocks and overestimates correlations between bond / commodity and stocks when markets are instable. This confirms that the traditional MV optimisation using the full covariance matrix tends to underweight bonds in times of financial instability and overweight them at other times.

7.4.4 Volatility Filter Rule

The underlying correlations are so different between volatility regimes that they can significantly affect the optimal weights at different times. We propose a dynamic rebalancing scheme where the underlying market volatility functions as a timing device and the underlying global portfolio is only rebalanced when the underlying volatility regime changes. The global

[47] The volatility threshold is determined using in-sample data (02/01/1989 – 25/12/1991). We calculate the mean and standard deviation of the RiskMetrics volatility forecasts of MSCI USA during the in-sample period, and the volatility threshold is set as the mean plus one standard deviation.

portfolio is formed from an U.S. investor's perspective, so we arbitrarily set the volatility forecast of the MSCI USA as an indicator to classify different volatility regimes: periods when volatility forecasts are higher than a certain threshold T are classified as times of financial instability with the remaining periods being "normal times". Let $\sigma^{(USA)}_{(t+1,t)}$ be the one step ahead forecast of MSCI USA volatility, a filtered portfolio rebalancing scheme can be described as:

$$\begin{cases} \text{if } \sigma^{(USA)}_{(t+1,t)} > T \quad \text{and} \quad \sigma^{(USA)}_{(t,t-1)} < T: & \text{Rebalance portfolio with new weights} \\ \text{if } \sigma^{(USA)}_{(t+1,t)} < T \quad \text{and} \quad \sigma^{(USA)}_{(t,t-1)} > T: & \text{Rebalance portfolio with new weights} \\ \text{Else}: & \text{No rebalancing} \end{cases}$$

7.4.5 Portfolio Rebalancing Strategies

In this chapter, we devise 4 dynamic and 1 static strategies to optimise portfolio weights based on the methodologies described above for empirical application. The portfolio weights of all the 4 dynamic rebalancing strategies are optimised every week in the review period (01/01/1992 to 29/12/2004) within the MV framework using one-week ahead return/covariance forecasts.

i.) The first 3 dynamic rebalancing strategies use RiskMetrics forecasts of conditional covariance as expected variance/covariance. Their respective return assumptions are:

- The RAER strategy expresses the expected return as a linear function of the risk incurred through a risk-aversion coefficient as in equation (7.4).

- The historical mean strategy uses the period return (in our case the previous week's return) as the expected return for the next period (week).
- The minimum variance strategy does not include any constraints on expected return and the optimal weights are those with the minimum expected portfolio variances.

ii.) In addition to the RiskMetrics approach, we also use the rollover approach to estimate the unconditional covariance matrix. This approach utilises the rolling historical mean and covariance. In this chapter, we set the rolling window size at 12 with the reason explained before, and the mean-variance forecasts for next period are the mean and variance estimated with the data of the previous 12 weeks[48].

iii.) A constant weighting scheme is also built and the equally weighted strategy does not change asset weights over time. For simplicity, this strategy assigns weights equally (20%) to each component asset.

We apply both the unconstrained and constrained strategies with respect to short-selling to the above rebalancing schemes. Since the equally weighted strategy retains the same weights at all times, which is to be long each asset at 20%, the short-selling constraint is irrelevant in this case.

[48] Except the minimum variance strategy, where the optimal weights are those with the minimum expected portfolio variance, the other 3 dynamic strategies calculate optimal maximizing the expected Information ratios. The weekly forecasts and allocations are programmed with Excel VBA to loop the procedure.

7.5 Empirical Results

Table 7.2 Portfolio performance statistics without volatility filters before transaction costs

* Full review period 01/01/1992 to 29/12/2004

	RAER	Historical Mean	Minimum Variance	Rollover	Equally Weighted
	CONSTRAINED AGAINST SHORT-SELLING				
Annualised Return	7.40%	0.61%	0.59%	6.42%	5.26%
Annualised Volatility	8.99%	12.54%	3.69%	9.68%	9.46%
Maximum Drawdown	-19.98%	-48.47%	-11.64%	-23.07%	-37.02%
Information Ratio	0.82	0.05	0.16	0.66	0.56
	UNCONSTRAINED				
Annualised Return	11.86%	-9.12%	0.11%	9.39%	5.26%
Annualised Volatility	15.74%	17.84%	3.71%	16.81%	9.46%
Maximum Drawdown	-24.10%	-156.39%	-14.26%	-38.63%	-37.02%
Information Ratio	0.75	-0.51	0.03	0.56	0.54

Table 7.2 shows the portfolio performances for the full review period from 01/01/1992 to 29/12/2004. The proposed RAER dynamic rebalancing approach has provided the best performance in terms of annualised return and risk-adjusted information ratio, while the minimum variance approach, as expected has the lowest risk features in terms of volatility and maximum drawdown. Dynamic rebalancing schemes with traditional minimum variance and historical mean approach fail to outperform the simple equally weighted portfolio, this result is in line with previous research such as Jobson and Korkie (1981) claiming the poor ex-post performance of MV optimisation. Nevertheless, both the RAER and rollover approaches outperform the

equally weighted portfolio significantly for the 13-year period in terms of information ratio, which suggests that the dynamic approach with accurate forecasts potentially adds value.

But dynamic portfolio rebalancing involves frequent transformation of asset weights, and the benefits from dynamic rebalancing can be quickly erased by transaction costs. Following Pesaran and Timmermann (1995), we set transaction costs as 0.5% per round trading on stocks and 0.1% on bonds[49]. To measure the consistency of performance, the entire review period is further equally split into 3 sub-periods. All performance measures after deduction of transaction costs are displayed in appendix table A.43. As expected, all measures for dynamic schemes deteriorate after transaction costs are included. As a matter of fact, all dynamic rebalancing approaches then underperform the equally weighted portfolio. Among these dynamic approaches, the proposed RAER approach prevails over others and the constrained RAER is the only portfolio producing positive returns and information ratios in all periods considered.

Simple dynamic rebalancing schemes are shown as costly. The existence of international contagion suggests a covariance matrix regime change between normal times and financial instability. This provides an opportunity to use a volatility filter to screen off unnecessary weight changes and the portfolio is only rebalanced when the underlying volatility regime changes. Table 7.3 shows the performance measures when the volatility filters described in

[49] For simplicity, transaction costs for commodities are set the same level as that of stocks at 0.5% per round trip, while in reality much lower transaction costs can be obtained in the futures markets.

section 7.4.4 above are superimposed on the simple dynamic rebalancing approaches.

Table 7.3 Portfolio performance statistics with volatility filters after transaction costs

	CONSTRAINED AGAINST SHORT SELLING				UNCONSTRAINED			
	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04
RAER								
Information Ratio	1.06	1.21	1.22	0.69	0.62	0.11	0.84	0.85
Maximum Drawdown	-13.32%	-8.77%	-8.79%	-13.32%	-39.77%	-39.37%	-39.77%	-14.19%
Historical Mean								
Information Ratio	0.37	0.40	0.00	0.74	-0.19	-0.14	-1.11	0.62
Maximum Drawdown	-43.04%	-35.51%	-43.04%	-22.29%	-128.21%	-45.13%	-89.92%	-18.63%
Minimum Variance								
Information Ratio	0.12	-0.13	0.04	0.49	0.05	-0.33	0.05	0.49
Maximum Drawdown	-12.15%	-12.15%	-6.35%	-4.81%	-13.76%	-13.76%	-6.81%	-4.81%
Rollover								
Information Ratio	1.08	1.21	1.30	0.64	0.40	-0.04	1.04	0.76
Maximum Drawdown	-8.90%	-8.82%	-8.90%	-6.56%	-84.41%	-84.41%	-24.83%	-7.40%
Equally Weighted								
Information Ratio	0.56	0.90	0.85	0.07				
Maximum Drawdown	-37.02%	-8.62%	-11.03%	-36.97%				

For simplicity, table 7.3 only presents the information ratios and maximum drawdowns. Further performance measures for portfolios with volatility filters can be found in appendix table A.44. It is obvious that the addition of a volatility filter adds significant value to portfolio performance in terms of annualised return, maximum drawdown and risk-adjusted information ratio in the entire review period as well as the 3 sub-periods chosen. With the addition of a volatility filter, the proposed RAER approach produces the most consistent performance with and without the constraint on short-selling compared to other dynamic rebalancing approaches. Both the filtered RAER and rollover approaches, with the constraint on short-selling outperform the equally weighted portfolio. Moreover, the information ratios obtained from the constrained RAER and rollover approaches using the filters are also consistently satisfactory, suggesting that the performance results obtained are not only good in relative terms when compared to alternative models, they are also actionable in a trading environment.

As far as short-selling constraint is concerned, though all unconstrained portfolios increase volatility by going short albeit moderately in some cases, we do not find that to go short contributes a significant return enhancement, as in most cases performances with short-selling are lower in terms of risk-adjusted measures. In reality, to short sell stocks in cash markets will incur higher transaction costs, and we therefore conclude that MV optimisations with short-selling constraints are more favourable than unconstrained ones.

7.6 Concluding Remarks

Volatilities and correlations of international stock markets are known to increase in times of financial instability. In this chapter, we proposed a dynamic rebalancing scheme where the underlying market volatility functions as a timing device for portfolio reallocation and the portfolio is only rebalanced when the underlying volatility regime changes. Significant improvements on portfolio performance in terms of annualised return, maximum drawdown and risk-adjusted information ratio have been found with the addition of such filters in the entire review period and all the sub-periods. Among all the portfolio rebalancing strategies studied, the proposed RAER approach produces the most consistent performance with and without the constraint on short-selling.

Overall unconstrained portfolios underperform portfolios with the constraint on short-selling. Considering the higher transaction costs incurred to short sell stocks in cash markets, we conclude that MV optimisations preventing short-selling are more favourable than the unconstrained ones. Of course, due to their flexibility, it is also possible and easy for market practitioners to include other constraints, for instance, to set a minimum weight for a specific asset.

Finally, the information ratios obtained from the constrained RAER and rollover approaches using the filters are satisfactory suggesting that these strategies are also actionable in a trading environment. The method studied in this chapter is also easy to implement, and has therefore significant merits in helping fund managers who need to rebalance their portfolios regularly.

CHAPTER 8

General Conclusion

Technical trading rules have been used in financial markets for decades, and are still one of the most popular forecasting techniques in financial markets. Among these, technical trending systems are quite popular, but are known to perform poorly in volatile markets. The primary motivation of the thesis was to investigate the performance of technical trending systems and other trading strategies in different volatility regimes. The thesis then proposed volatility filters to enhance the performance of such strategies.

Two volatility filters were proposed, namely a "no-trade" filter where all market positions are closed in volatile periods, and a "reverse" filter where signals from the original trading strategies are reversed if market volatility is higher than a given threshold.

Our results show that the addition of the two volatility filters has significantly improved the performance of trend-following MACD systems at both the single asset and portfolio level. Besides, similar results have been found when volatility filters are applied to two portfolios which are highly correlated with a managed futures index and a currency traders' performance benchmark. When the two volatility filters are concerned, although the "reverse" strategy outperforms in terms of risk-adjusted information ratio most of the time, investors following a "no-trade" strategy are able to free up funds out of highly volatile markets and invest into other markets for short-term profits. In this respect, there is no "winning" of one filter against the other and it is up to investors to choose the right strategy based on their risk tolerance. Based on the findings from above study, the optimal trading frequencies for some most heavily traded currency and futures products have also been identified.

In addition, we have also found some interesting results for the first time regarding the predictability of trend-following systems. Firstly, with no previous articles comparing the predictability of technical trading rules in different markets, our results showed that technical trading rules seem to work better in stock and currency markets than they do in bond and commodity markets. Secondly, departing from the previous literature, which compares the performances between MACDs with different window length, we also compared the impact of volatility regime changes on MACDs with different window length. We found that MACDs consisting of short-term MAs tend to outperform those MACDs with long-term MAs when the market is relatively stable, while the latter perform better in more volatile periods. We then proposed a model switch strategy, where signals from different MACD systems are taken depending on the prevailing market volatility.

As for the alternative trading strategies studied in this thesis, our results show that a carry model performs poorly when market volatility is high and the addition of volatility filters then enhances the performance of the carry model, which also outperforms a benchmark dynamic MACD model. Generally, a spectral model built on the cyclical spectral properties of exchange rates performs poorly across different volatility regimes, and there is no evidence that the performance of this model is affected by volatility regime changes. Yet, a trading strategy combining volatility and spectral filters significantly improves the performance of traditional technical trading models for active currency portfolio management.

Finally, the thesis proposed a dynamic rebalancing scheme where the underlying market volatility functions as a timing device for portfolio reallocation and portfolio is only rebalanced when the underlying volatility regime changes. Significant improvements on portfolio performance in terms of annualised return, maximum drawdown and risk-adjusted information ratio have been found with the addition of such filters in the entire review period and all the sub-periods. Among all the portfolio rebalancing strategies studied, the proposed RAER approach produces the most consistent performance with and without the constraint on short-selling. This is the first time that the well-known phenomena of international contagion and volatility regime changes are applied in the context of dynamic portfolio rebalancing.

The results of this thesis open a number of potential areas for future research. A natural extension of the thesis is to study whether underlying volatility regimes have a significant impact on other contemporary quantitative forecasting models or trading techniques. In addition, the availability of intraday data has generated a lot of concerns in the area of empirical finance. Since intraday data on securities and exchange rates provide a rich testing ground for the study of microstructural effects of information flows on prices and trading activities (see, among others, Low & Muthuswany 1996), it would

LIVER

be interesting to investigate the relationships between market volatilities and alternative trading strategies at a microstructure level.

In conclusion, some of the most widely used trading strategies are found to perform poorly when markets are highly volatile, and adaptive strategies like the volatility filters proposed in this thesis should be adopted during those periods to enhance trading performance. In addition, correlations between international financial markets change significantly with changes in these markets volatility regimes. Volatility filters based on these volatility regime changes can play as an effective timing device for dynamic portfolio optimisation and rebalancing.

Appendix

Table A.1 Statistics of market volatility in different subperiods

	6-year Period (17/12/98 - 30/03/04)		3-year Period (02/01/01 - 30/03/04)		Year 2003 (02/01/03 - 31/12/03)		Half Year (01/09/03 - 30/03/04)	
	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.
SP500	19.98%	6.27%	20.00%	7.19%	16.25%	4.51%	11.03%	1.60%
EUR/USD	9.84%	1.92%	9.80%	1.96%	9.28%	0.97%	10.27%	1.58%
COPP.	17.43%	4.42%	16.75%	3.86%	15.74%	1.82%	19.27%	5.92%
OILB	35.97%	8.87%	34.34%	9.24%	33.90%	7.36%	30.31%	2.91%
BUND	5.39%	1.41%	5.23%	1.31%	6.24%	1.12%	5.43%	1.17%

	6-year Period (17/12/98 - 30/03/04)		3-year Period (02/01/01 - 30/03/04)		Year 2003 (02/01/03 - 31/12/03)		Half Year (01/09/03 - 30/03/04)	
	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.	Average Vol.	Std. Dev.
USD/JPY	9.90%	2.32%	9.17%	1.68%	8.63%	1.18%	8.26%	1.97%
GBP/USD	7.42%	1.66%	7.48%	1.72%	7.51%	1.18%	8.40%	2.49%
ALUMINUM	14.20%	3.41%	13.31%	3.52%	11.81%	1.47%	13.08%	2.52%
STOXX50	27.16%	10.58%	29.83%	12.08%	29.08%	10.39%	17.37%	4.08%
T-BOND	9.89%	2.30%	10.83%	2.23%	12.01%	2.53%	12.34%	2.28%

Table A.2 Performance statistics for FX portfolio (with single MACD) _Transaction costs at 0.02%

	10-year Period (18/12/1995 - 30/03/2004)				5-year Period (02/01/1999 - 30/03/2004)				Year 2003 (02/01/2003 - 31/12/2003)				Half Year (01/09/2002 - 30/03/2004)			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1D- 5D	63	2.52%	0.46	-6.23%	61	3.62%	0.63	-6.23%	59	4.98%	0.89	-4.76%	55	5.84%	0.89	-3.29%
1D- 32D	23	2.35%	0.41	-8.59%	23	1.96%	0.32	-8.59%	22	7.95%	1.37	-3.49%	20	6.68%	1.00	-4.68%
1D- 61D	14	3.97%	0.67	-7.63%	14	3.89%	0.63	-7.63%	13	9.04%	1.50	-5.22%	9	9.96%	1.40	-3.81%
1D- 117 D	12	1.07%	0.18	-12.95%	13	0.23%	0.04	-12.95%	13	6.87%	1.15	-5.71%	13	3.47%	0.49	-6.43%
1D- 250 D	6	4.24%	0.72	-9.99%	6	4.19%	0.67	-9.99%	4	11.97%	1.83	-6.15%	4	15.20%	1.98	-4.80%
Strategy #2	*MACD with No-trade volatility filter*															
1D- 5D	54	3.59%	0.80	-6.27%	53	4.18%	0.87	-6.27%	57	4.42%	0.81	-4.46%	45	13.72%	2.48	-1.92%
1D- 32D	21	3.34%	0.71	-6.90%	22	3.29%	0.65	-6.20%	22	7.53%	1.33	-3.58%	19	7.36%	1.30	-4.45%
1D- 61D	15	4.42%	0.92	-5.84%	16	5.26%	1.02	-5.84%	15	9.26%	1.59	-4.47%	11	10.73%	1.81	-2.94%
1D- 117 D	13	1.72%	0.36	-11.09%	13	1.70%	0.33	-11.09%	14	6.74%	1.16	-5.39%	10	5.77%	0.97	-4.60%
1D- 250 D	9	4.63%	0.95	-8.20%	9	4.87%	0.93	-8.20%	6	11.61%	1.83	-5.57%	8	12.95%	2.13	-4.53%
Strategy #3	*MACD with Reverse volatility filter*															
1D- 5D	66	4.24%	0.85	-6.96%	65	4.33%	0.83	-6.96%	60	3.74%	0.68	-4.47%	60	21.11%	3.54	-1.93%
1D- 32D	29	4.17%	0.81	-9.11%	29	4.45%	0.82	-4.82%	25	7.06%	1.26	-3.81%	25	7.91%	1.25	-4.82%
1D- 61D	21	4.79%	0.91	-8.00%	22	6.54%	1.19	-4.69%	18	9.44%	1.65	-3.80%	17	11.38%	1.84	-3.18%
1D- 117 D	19	2.28%	0.43	-11.70%	19	3.06%	0.56	-11.70%	17	6.58%	1.15	-5.07%	20	7.84%	1.32	-4.65%
1D- 250 D	14	4.98%	0.94	-7.99%	15	5.51%	0.98	-7.99%	10	11.23%	1.80	-5.33%	13	10.67%	1.72	-6.16%
FX Benchmark	**16**	**2.46%**	**0.48**	**-8.88%**	**16**	**2.03%**	**0.37**	**-8.88%**	**16**	**7.95%**	**1.48**	**-4.33%**	**14**	**6.70%**	**1.09**	**-4.54%**

Table A.3 Performance statistics for FX portfolio (with single MACD) _Transaction costs at 0.01%

	10-year Period (18/12/1995 - 30/03/2004)				*5-year Period (02/01/1999 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2002 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1D- 5D	63	3.15%	0.57	-6.23%	61	4.23%	0.74	-6.23%	59	5.57%	1.00	-4.76%	55	6.39%	0.97	-3.29%
1D- 32D	23	2.57%	0.44	-8.59%	23	2.18%	0.36	-8.59%	22	8.17%	1.40	-3.49%	20	6.88%	1.03	-4.68%
1D- 61D	14	4.11%	0.70	-7.63%	14	4.03%	0.65	-7.63%	13	9.17%	1.52	-5.22%	9	10.05%	1.42	-3.81%
1D- 117 D	12	1.19%	0.20	-12.95%	13	0.35%	0.06	-12.95%	13	6.99%	1.17	-5.71%	13	3.60%	0.51	-6.43%
1D- 250 D	6	4.30%	0.73	-9.99%	6	4.25%	0.68	-9.99%	4	12.01%	1.84	-6.15%	4	15.24%	1.98	-4.80%
Strategy #2	*MACD with No-trade volatility filter*															
1D- 5D	54	4.13%	0.92	-6.27%	53	4.70%	0.98	-6.27%	57	4.98%	0.91	-4.46%	45	14.17%	2.56	-1.92%
1D- 32D	21	3.56%	0.75	-6.90%	22	3.51%	0.69	-6.20%	22	7.75%	1.37	-3.58%	19	7.55%	1.33	-4.45%
1D- 61D	15	4.57%	0.95	-5.84%	16	5.42%	1.05	-5.84%	15	9.41%	1.62	-4.47%	11	10.83%	1.83	-2.94%
1D- 117 D	13	1.85%	0.39	-11.09%	13	1.83%	0.35	-11.09%	14	6.88%	1.18	-5.39%	10	5.88%	0.99	-4.60%
1D- 250 D	9	4.72%	0.97	-8.20%	9	4.96%	0.94	-8.20%	6	11.67%	1.84	-5.57%	8	13.03%	2.14	-4.53%
Strategy #3	*MACD with Reverse volatility filter*															
1D- 5D	66	4.90%	0.98	-6.96%	65	4.97%	0.95	-6.96%	60	4.34%	0.79	-4.47%	60	21.71%	3.64	-1.93%
1D- 32D	29	4.46%	0.86	-9.11%	29	4.75%	0.88	-4.82%	25	7.30%	1.31	-3.81%	25	8.16%	1.29	-4.82%
1D- 61D	21	5.00%	0.95	-8.00%	22	6.76%	1.23	-4.69%	18	9.62%	1.69	-3.80%	17	11.55%	1.87	-3.18%
1D- 117 D	19	2.47%	0.47	-11.70%	19	3.25%	0.59	-11.70%	17	6.75%	1.18	-5.07%	20	8.04%	1.35	-4.65%
1D- 250 D	14	5.12%	0.96	-7.99%	15	5.65%	1.01	-7.99%	10	11.32%	1.81	-5.33%	13	10.80%	1.74	-6.16%
FX Benchmark	**16**	**2.63%**	**0.51**	**-8.88%**	**16**	**2.19%**	**0.40**	**-8.88%**	**16**	**8.11%**	**1.51**	**-4.33%**	**14**	**6.85%**	**1.12**	**-4.54%**

Table A.4 Performance statistics for FX portfolio (with combined MACD) _Transaction costs at 0.02%

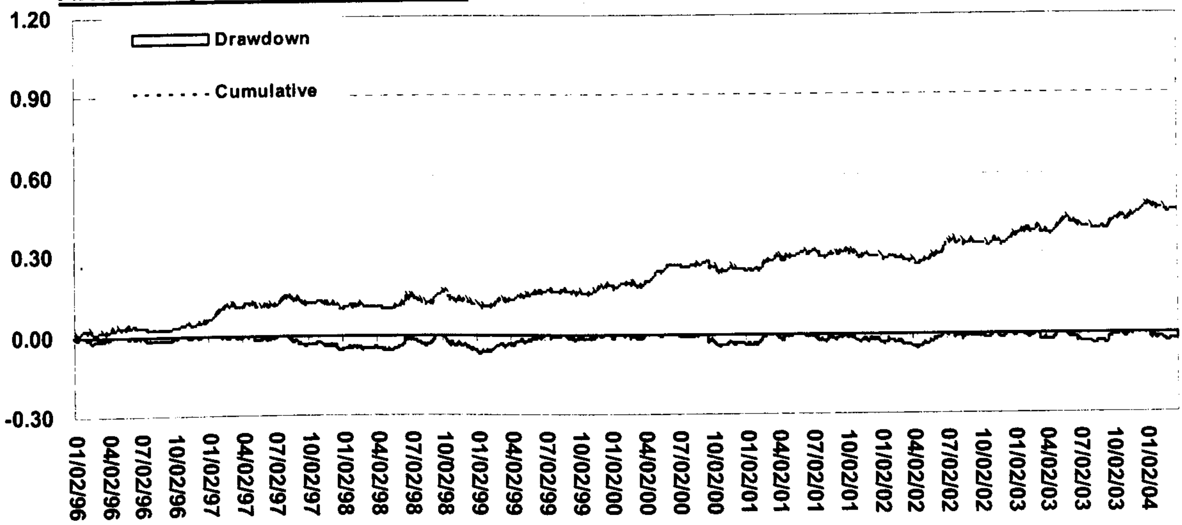
	10-year Period (18/12/1995 - 30/03/2004)				*5-year Period (02/01/1999 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2002 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-15 D / 1-25 D / 1-61 D	24	3.20%	0.63	-7.48%	24	3.00%	0.57	-7.48%	22	8.40%	1.63	-3.88%	20	8.85%	1.52	-3.74%
1-32 D / 1-61 D / 1-117D	16	2.46%	0.48	-8.88%	16	2.03%	0.37	-8.88%	16	7.95%	1.48	-4.33%	14	6.70%	1.09	-4.54%
1-32 D / 1-61D	18	3.16%	0.58	-7.85%	18	2.93%	0.51	-7.85%	18	8.50%	1.51	-3.88%	15	8.32%	1.27	-4.01%
1-61 D / 1-250 D	10	4.11%	0.78	-7.01%	10	4.04%	0.73	-7.01%	9	10.51%	1.89	-4.75%	6	12.60%	1.99	-3.32%
Strategy #2	*MACD with No-trade volatility filter*															
1-15 D / 1-25 D / 1-61 D	22	4.10%	0.98	-4.31%	23	4.32%	0.96	-4.06%	23	8.67%	1.73	-3.64%	17	13.03%	2.68	-2.55%
1-32 D / 1-61 D / 1-117D	16	3.18%	0.74	-5.62%	16	3.44%	0.74	-5.62%	17	7.85%	1.50	-4.10%	13	7.97%	1.48	-3.33%
1-32 D / 1-61D	18	3.89%	0.86	-5.00%	18	4.29%	0.88	-5.00%	18	8.40%	1.55	-3.64%	14	9.06%	1.66	-3.16%
1-61 D / 1-250 D	11	4.55%	1.05	-6.29%	11	5.09%	1.09	-6.29%	10	10.44%	1.94	-4.30%	8	11.86%	2.10	-2.84%
Strategy #3	*MACD with Reverse volatility filter*															
1-15 D / 1-25 D / 1-61 D	29	4.83%	1.08	-6.02%	30	5.47%	1.17	-3.43%	25	8.89%	1.78	-3.43%	25	16.97%	3.15	-2.23%
1-32 D / 1-61 D / 1-117D	22	3.77%	0.82	-6.11%	22	4.71%	0.98	-5.19%	20	7.70%	1.50	-3.86%	20	9.06%	1.71	-3.72%
1-32 D / 1-61D	24	4.50%	0.93	-6.37%	25	5.51%	1.09	-3.89%	21	8.26%	1.55	-3.45%	20	9.66%	1.64	-3.89%
1-61 D / 1-250 D	15	4.92%	1.05	-6.62%	16	6.07%	1.23	-5.56%	13	10.35%	1.95	-3.86%	13	11.07%	2.10	-3.40%
FX Benchmark	**16**	**2.46%**	**0.48**	**-8.88%**	**16**	**2.03%**	**0.37**	**-8.88%**	**16**	**7.95%**	**1.48**	**-4.33%**	**14**	**6.70%**	**1.09**	**-4.54%**

Table A.5 Performance statistics for FX portfolio (with combined MACD) _Transaction costs at 0.01%

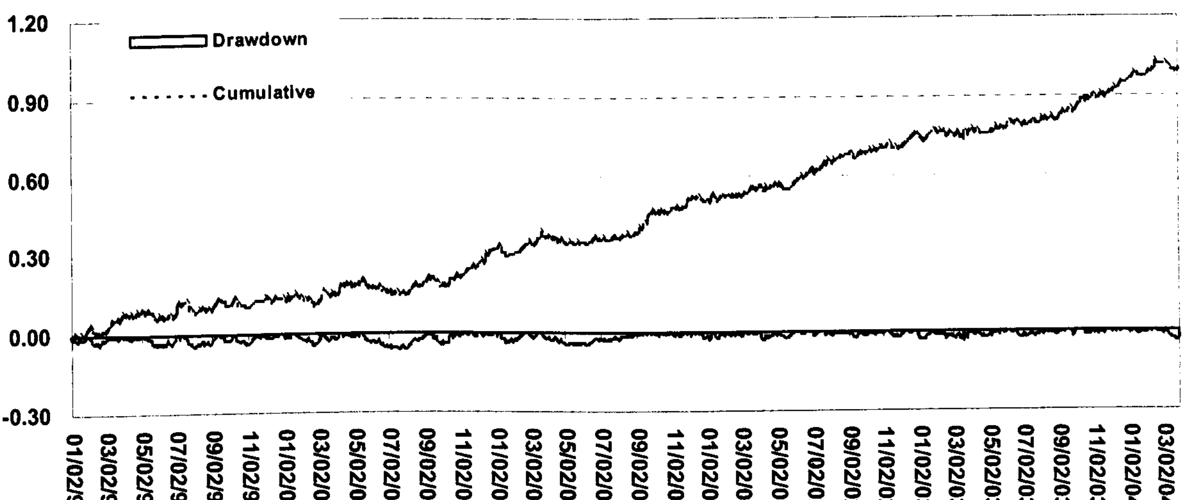
	10-year Period (18/12/1995 - 30/03/2004)				*5-year Period (02/01/1999 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2002 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-15 D / 1-25 D / 1-61 D	24	3.44%	0.68	-7.48%	24	3.25%	0.62	-7.48%	22	8.62%	1.68	-3.88%	20	9.05%	1.56	-3.74%
1-32 D / 1-61 D / 1-117D	16	2.63%	0.51	-8.88%	16	2.19%	0.40	-8.88%	16	8.11%	1.51	-4.33%	14	6.85%	1.12	-4.54%
1-32 D / 1-61D	18	3.34%	0.61	-7.85%	18	3.11%	0.54	-7.85%	18	8.67%	1.55	-3.88%	15	8.47%	1.29	-4.01%
1-61 D / 1-250 D	10	4.20%	0.80	-7.01%	10	4.14%	0.75	-7.01%	9	10.59%	1.91	-4.75%	6	12.66%	2.00	-3.32%
Strategy #2	*MACD with No-trade volatility filter*															
1-15 D / 1-25 D / 1-61 D	22	4.33%	1.03	-4.31%	23	4.55%	1.01	-4.06%	23	8.90%	1.77	-3.64%	17	13.20%	2.71	-2.55%
1-32 D / 1-61 D / 1-117D	16	3.34%	0.78	-5.62%	16	3.60%	0.77	-5.62%	17	8.02%	1.54	-4.10%	13	8.10%	1.50	-3.33%
1-32 D / 1-61D	18	4.07%	0.90	-5.00%	18	4.47%	0.92	-5.00%	18	8.58%	1.58	-3.64%	14	9.20%	1.69	-3.16%
1-61 D / 1-250 D	11	4.66%	1.07	-6.29%	11	5.20%	1.11	-6.29%	10	10.54%	1.96	-4.30%	8	11.94%	2.12	-2.84%
Strategy #3	*MACD with Reverse volatility filter*															
1-15 D / 1-25 D / 1-61 D	29	5.12%	1.14	-6.02%	30	5.77%	1.23	-3.43%	25	9.14%	1.83	-3.43%	25	17.22%	3.20	-2.23%
1-32 D / 1-61 D / 1-117D	22	3.99%	0.87	-6.11%	22	4.93%	1.03	-5.19%	20	7.90%	1.54	-3.86%	20	9.26%	1.75	-3.72%
1-32 D / 1-61D	24	4.74%	0.98	-6.37%	25	5.76%	1.14	-3.89%	21	8.47%	1.59	-3.45%	20	9.87%	1.67	-3.89%
1-61 D / 1-250 D	15	5.08%	1.09	-6.62%	16	6.23%	1.26	-5.56%	13	10.48%	1.98	-3.86%	13	11.20%	2.12	-3.40%
FX Benchmark	**16**	**2.63%**	**0.51**	**-8.88%**	**16**	**2.19%**	**0.40**	**-8.88%**	**16**	**8.11%**	**1.51**	**-4.33%**	**14**	**6.85%**	**1.12**	**-4.54%**

Figure A.1 Net cumulative return and maximum drawdown of the "optimal" strategy with the addition of the "reverse" filter

A.1.a FX portfolio performance



A.1.b Portfolio 2 performance



A.1.a Portfolio 3 performance

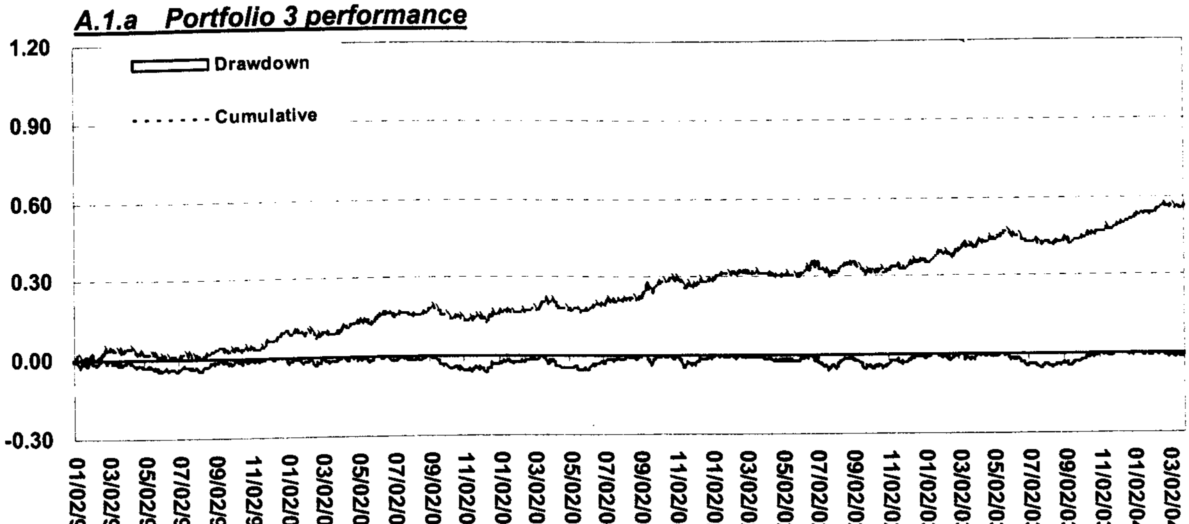


Table A.6 Performance statistics for S&P500 futures

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-30 D & 25-250 D	11	4.33%	0.26	-27.54%	9	12.43%	0.70	-21.90%	9	16.37%	1.29	-5.61%	8	17.16%	2.10	-3.08%
1-32 D / 1-61 D / 1-117D	16	-7.67%	-0.41	-63.35%	13	3.56%	0.19	-34.34%	11	10.73%	0.73	-12.36%	7	16.51%	1.87	-3.13%
5-250 D & 25-250 D	1	11.83%	0.58	-19.46%	1	14.67%	0.70	-19.46%	2	12.80%	0.80	-15.14%	2	24.91%	2.28	-5.76%
Model Switch	2	13.55%	0.65	-20.80%	1	14.59%	0.69	-20.80%	2	14.26%	0.88	-14.18%	2	24.91%	2.28	-5.76%
Strategy #2	*MACD with No-trade volatility filter*															
1-30 D & 25-250 D	11	7.97%	0.50	-27.54%	9	18.34%	1.10	-16.23%	9	16.37%	1.29	-5.61%	8	17.16%	2.10	-3.08%
1-32 D / 1-61 D / 1-117D	16	-3.55%	-0.20	-63.06%	13	10.18%	0.58	-22.98%	11	10.73%	0.73	-12.36%	7	16.51%	1.87	-3.13%
5-250 D & 25-250 D	2	15.89%	0.81	-19.38%	2	21.04%	1.08	-19.38%	2	12.80%	0.80	-15.14%	2	24.91%	2.28	-5.76%
Model Switch	3	17.60%	0.88	-20.80%	2	20.96%	1.07	-20.80%	2	14.26%	0.88	-14.18%	2	24.91%	2.28	-5.76%
Strategy #3	*MACD with Reverse volatility filter*															
1-30 D & 25-250 D	12	11.51%	0.69	-27.54%	10	24.10%	1.35	-16.23%	9	16.37%	1.29	-5.61%	8	17.16%	2.10	-3.08%
1-32 D / 1-61 D / 1-117D	17	0.44%	0.02	-62.78%	14	16.58%	0.89	-22.98%	11	10.73%	0.73	-12.36%	7	16.51%	1.87	-3.13%
5-250 D & 25-250 D	3	19.94%	0.97	-19.38%	3	27.41%	1.31	-19.38%	2	12.80%	0.80	-15.14%	2	24.91%	2.28	-5.76%
Model Switch	4	21.66%	1.04	-20.80%	3	27.33%	1.30	-20.80%	2	14.26%	0.88	-14.18%	2	24.91%	2.28	-5.76%
Buy & Hold	**0**	**1.10%**	**0.05**	**-62.75%**	**0**	**-2.93%**	**-0.14**	**-52.68%**	**1**	**23.96%**	**1.48**	**-14.80%**	**2**	**24.91%**	**2.28**	**-5.76%**

Table A.7 ***Performance statistics for STOXX50 futures***

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-30 D & 25-250 D	13	5.80%	0.24	-39.55%	12	10.69%	0.39	-36.76%	18	-9.77%	-0.41	-36.76%	12	10.46%	0.85	-4.35%
5-250 D & 25-250 D	1	19.46%	0.67	-37.04%	1	18.92%	0.59	-37.04%	2	6.36%	0.21	-37.04%	2	27.45%	1.58	-10.27%
1-32 D / 1-61 D / 1-117D	20	-9.20%	-0.35	-65.32%	18	-5.36%	-0.19	-57.50%	22	-16.32%	-0.61	-37.28%	19	-8.47%	-0.56	-6.94%
Model Switch	1	18.57%	0.64	-39.84%	1	18.08%	0.56	-39.84%	2	3.64%	0.12	-39.84%	2	27.45%	1.58	-10.27%
Strategy #2	*MACD with No-trade volatility filter*															
1-30 D & 25-250 D	12	8.18%	0.41	-39.55%	11	14.56%	0.72	-22.40%	16	4.43%	0.21	-22.40%	12	10.46%	0.85	-4.35%
5-250 D & 25-250 D	2	22.10%	0.94	-20.68%	2	23.21%	0.98	-17.97%	3	25.10%	0.97	-17.66%	2	27.45%	1.58	-10.27%
1-32 D / 1-61 D / 1-117D	19	-4.59%	-0.21	-51.56%	16	2.15%	0.10	-37.01%	20	-0.51%	-0.02	-21.28%	19	-8.47%	-0.56	-6.94%
Model Switch	2	21.20%	0.90	-22.61%	2	22.37%	0.94	-20.46%	3	22.38%	0.86	-20.46%	2	27.45%	1.58	-10.27%
Strategy #3	*MACD with Reverse volatility filter*															
1-30 D & 25-250 D	14	10.29%	0.42	-39.55%	13	18.00%	0.66	-37.94%	18	18.05%	0.76	-14.04%	12	10.46%	0.85	-4.35%
5-250 D & 25-250 D	3	24.74%	0.85	-46.32%	4	27.50%	0.86	-46.32%	4	43.84%	1.48	-14.14%	2	27.45%	1.58	-10.27%
1-32 D / 1-61 D / 1-117D	21	-0.37%	-0.01	-51.56%	20	9.00%	0.32	-45.36%	23	14.68%	0.55	-15.11%	19	-8.47%	-0.56	-6.94%
Model Switch	3	23.84%	0.82	-46.32%	4	26.66%	0.83	-46.32%	4	41.12%	1.38	-16.93%	2	27.45%	1.58	-10.27%
Buy & Hold	**0**	**1.47%**	**0.05**	**-96.26%**	**0**	**-11.72%**	**-0.37**	**-85.26%**	**1**	**18.98%**	**0.63**	**-34.25%**	**2**	**27.45%**	**1.58**	**-10.27%**

Table A.8 Performance statistics for GBP/USD

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-61 D & 5-250 D	8	2.58%	0.38	-12.56%	8	3.34%	0.49	-11.98%	5	9.37%	1.51	-5.54%	6	13.55%	1.55	-6.89%
1-32 D / 1-61 D / 1-117D	16	1.45%	0.22	-15.89%	17	1.44%	0.22	-13.31%	13	8.87%	1.32	-4.76%	7	15.64%	1.95	-5.36%
1-61 D / 1-250 D	10	2.90%	0.42	-9.73%	9	4.09%	0.60	-9.15%	8	9.07%	1.46	-5.53%	6	13.55%	1.55	-6.89%
Switch	10	3.53%	0.46	-12.09%	10	6.25%	0.81	-12.09%	11	11.37%	1.51	-6.37%	2	19.12%	2.01	-5.99%
Strategy #2	*MACD with No-trade volatility filter*															
1-61 D & 5-250 D	9	3.43%	0.52	-12.09%	9	4.59%	0.70	-11.98%	5	9.37%	1.51	-5.54%	8	21.19%	2.90	-3.58%
1-32 D / 1-61 D / 1-117D	17	1.98%	0.30	-15.32%	18	2.13%	0.33	-13.31%	13	8.87%	1.32	-4.76%	9	19.98%	2.77	-3.58%
1-61 D / 1-250 D	10	3.75%	0.56	-9.26%	10	5.34%	0.82	-9.15%	8	9.07%	1.46	-5.53%	8	21.19%	2.90	-3.58%
Switch	11	3.74%	0.50	-12.09%	11	6.65%	0.90	-12.09%	11	11.37%	1.51	-6.37%	8	21.19%	2.90	-3.58%
Strategy #3	*MACD with Reverse volatility filter*															
1-61 D & 5-250 D	11	4.27%	0.62	-11.98%	11	5.82%	0.86	-11.98%	5	9.37%	1.51	-5.54%	20	28.73%	3.34	-3.87%
1-32 D / 1-61 D / 1-117D	18	2.50%	0.38	-14.75%	20	2.81%	0.42	-13.31%	13	8.87%	1.32	-4.76%	20	24.23%	3.05	-3.87%
1-61 D / 1-250 D	12	4.59%	0.67	-9.15%	12	6.57%	0.97	-9.15%	8	9.07%	1.46	-5.53%	20	28.73%	3.34	-3.87%
Switch	13	3.95%	0.52	-12.09%	13	7.05%	0.91	-12.09%	11	11.37%	1.51	-6.37%	16	23.24%	2.45	-3.87%
Benchmark	**16**	**1.45%**	**0.22**	**-15.89%**	**17**	**1.44%**	**0.22**	**-13.31%**	**13**	**8.87%**	**1.32**	**-4.76%**	**7**	**15.64%**	**1.95**	**-5.36%**

Table A.9 Performance statistics for USD/JPY

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-61 D & 1-250 D	9	3.01%	0.36	-19.73%	8	5.35%	0.70	-10.77%	15	2.09%	0.28	-8.01%	4	9.27%	1.35	-2.89%
1-32 D / 1-61 D / 1-117D	18	-0.32%	-0.04	-21.28%	17	1.48%	0.18	-21.28%	28	-5.49%	-0.72	-13.98%	14	2.98%	0.38	-5.37%
1-31 D & 5-250 D	13	2.03%	0.26	-16.89%	12	3.00%	0.44	-11.46%	18	0.73%	0.11	-7.78%	14	5.35%	0.86	-3.31%
Switch	6	5.36%	0.53	-14.91%	5	7.97%	0.85	-9.88%	9	9.89%	1.16	-3.53%	10	17.78%	2.09	-3.64%
Strategy #2	*MACD with No-trade volatility filter*															
1-61 D & 1-250 D	10	4.38%	0.60	-15.23%	9	6.93%	0.93	-9.55%	15	2.09%	0.28	-8.01%	4	9.27%	1.35	-2.89%
1-32 D / 1-61 D / 1-117D	17	2.66%	0.34	-18.09%	18	3.03%	0.38	-18.09%	28	-5.49%	-0.72	-13.98%	14	2.98%	0.38	-5.37%
1-32 D & 5-250 D	12	3.99%	0.58	-8.58%	13	4.22%	0.63	-8.58%	18	0.73%	0.11	-7.78%	14	5.35%	0.86	-3.31%
Switch	9	5.94%	0.66	-10.91%	8	8.85%	0.96	-10.91%	9	9.89%	1.16	-3.53%	10	17.78%	2.09	-3.64%
Strategy #3	*MACD with Reverse volatility filter*															
1-61 D & 1-250 D	13	5.74%	0.69	-14.62%	11	8.50%	1.12	-9.55%	15	2.09%	0.28	-8.01%	4	9.27%	1.35	-2.89%
1-32 D / 1-61 D / 1-117D	22	5.55%	0.63	-17.96%	20	4.56%	0.57	-17.96%	28	-5.49%	-0.72	-13.98%	14	2.98%	0.38	-5.37%
1-32 D & 5-250 D	16	5.88%	0.76	-7.78%	14	5.41%	0.80	-7.78%	18	0.73%	0.11	-7.78%	14	5.35%	0.86	-3.31%
Switch	12	6.51%	0.65	-13.38%	10	9.73%	1.04	-12.51%	9	9.89%	1.16	-3.53%	10	17.78%	2.09	-3.64%
Benchmark	**18**	**-0.32%**	**-0.04**	**-21.28%**	**17**	**1.48%**	**0.18**	**-21.28%**	**28**	**-5.49%**	**-0.72**	**-13.98%**	**14**	**2.98%**	**0.38**	**-5.37%**

Table A.10 Performance statistics for EUR/USD

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-61 D & 2-250 D	7	6.85%	0.77	-17.01%	9	4.42%	0.49	-15.70%	6	16.26%	2.00	-5.46%	2	13.06%	1.44	-3.71%
1-32 D / 1-61 D / 1-117D	14	5.39%	0.63	-15.54%	16	2.45%	0.30	-15.54%	11	14.87%	1.86	-4.89%	14	6.15%	0.71	-6.70%
1-61 D / 1-150 D	9	6.38%	0.72	-17.57%	11	3.23%	0.37	-17.57%	9	14.36%	1.65	-7.39%	2	13.06%	1.44	-3.71%
Model Switch	13	6.65%	0.66	-22.26%	14	4.13%	0.41	-15.59%	15	18.40%	1.97	-7.35%	2	9.41%	0.88	-5.81%
Strategy #2	*MACD with No-trade volatility filter*															
1-61 D & 2-250 D	9	7.44%	0.94	-14.06%	10	6.40%	0.81	-12.54%	6	16.26%	2.00	-5.46%	6	12.53%	1.39	-3.71%
1-32 D / 1-61 D / 1-117D	14	5.57%	0.71	-14.93%	15	4.65%	0.62	-11.47%	11	14.87%	1.86	-4.89%	11	8.90%	1.09	-5.47%
1-61 D / 1-150 D	10	6.73%	0.84	-15.05%	11	5.49%	0.70	-11.39%	9	14.36%	1.65	-7.39%	6	12.53%	1.39	-3.71%
Model Switch	15	8.10%	0.91	-13.37%	16	6.52%	0.75	-11.10%	15	18.40%	1.97	-7.35%	6	7.97%	0.85	-5.84%
Strategy #3	*MACD with Reverse volatility filter*															
1-61 D & 2-250 D	13	8.00%	0.90	-13.25%	15	8.35%	0.93	-12.42%	6	16.26%	2.00	-5.46%	10	12.00%	1.32	-4.26%
1-32 D / 1-61 D / 1-117D	20	5.70%	0.66	-17.97%	21	6.79%	0.82	-11.57%	11	14.87%	1.86	-4.89%	18	11.54%	1.33	-5.55%
1-61 D / 1-150 D	14	7.04%	0.79	-15.58%	15	7.69%	0.88	-11.27%	9	14.36%	1.65	-7.39%	10	12.00%	1.32	-4.26%
Model Switch	20	9.52%	0.95	-11.10%	21	8.87%	0.89	-11.10%	15	18.40%	1.97	-7.35%	12	6.50%	0.60	-8.45%
Benchmark	**14**	**5.39%**	**0.63**	**-15.54%**	**16**	**2.45%**	**0.30**	**-15.54%**	**11**	**14.87%**	**1.86**	**-4.89%**	**14**	**6.15%**	**0.71**	**-6.70%**

Table A.11 Performance statistics for aluminium futures

	6-year Period (17/12/1998 - 30/03/2004)				3-year Period (02/01/2001 - 30/03/2004)				Year 2003 (02/01/2003 - 31/12/2003)				Half Year (01/09/2003 - 30/03/2004)			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
5-100 D & 10-100 D	5	1.00%	0.07	-48.02%	7	-2.59%	-0.20	-33.28%	6	9.31%	0.82	-11.24%	2	35.36%	2.63	-7.35%
1-30 D & 5-100 D	13	0.30%	0.02	-36.69%	16	-5.65%	-0.49	-33.74%	15	8.41%	0.82	-5.02%	4	28.39%	2.32	-6.11%
1-32 D / 1-61 D / 1-117D	16	-3.35%	-0.27	-48.43%	19	-9.00%	-0.77	-41.16%	16	-1.11%	-0.11	-12.90%	7	25.13%	2.02	-7.65%
Model Switch	9	-1.26%	-0.09	-50.92%	11	-4.53%	-0.33	-37.67%	15	5.47%	0.46	-13.17%	2	35.36%	2.63	-7.35%
Strategy #2	*MACD with No-trade volatility filter*															
5-100 D & 10-100 D	7	4.08%	0.34	-21.79%	6	2.44%	0.21	-21.26%	6	9.31%	0.82	-11.24%	8	35.27%	2.75	-6.64%
1-30 D & 5-100 D	12	5.40%	0.53	-16.78%	13	1.77%	0.17	-16.78%	15	8.41%	0.82	-5.02%	6	30.74%	2.55	-4.80%
1-32 D / 1-61 D / 1-117D	14	2.02%	0.19	-24.67%	15	-1.54%	-0.15	-24.67%	16	-1.11%	-0.11	-12.90%	8	28.18%	2.32	-6.02%
Model Switch	10	3.60%	0.30	-19.82%	11	2.70%	0.23	-18.78%	15	5.47%	0.46	-13.17%	8	35.27%	2.75	-6.64%
Strategy #3	*MACD with Reverse volatility filter*															
5-100 D & 10-100 D	13	6.60%	0.46	-28.90%	10	6.89%	0.52	-17.82%	6	9.31%	0.82	-11.24%	14	35.17%	2.62	-7.09%
1-30 D & 5-100 D	18	9.65%	0.79	-17.05%	17	8.25%	0.71	-16.78%	15	8.41%	0.82	-5.02%	8	33.09%	2.71	-4.25%
1-32 D / 1-61 D / 1-117D	21	6.29%	0.51	-22.19%	21	4.67%	0.40	-22.19%	16	-1.11%	-0.11	-12.90%	12	30.91%	2.50	-5.16%
Model Switch	17	7.85%	0.54	-26.34%	15	9.32%	0.68	-15.33%	15	5.47%	0.46	-13.17%	14	35.17%	2.62	-7.09%
Buy & Hold	**0**	**6.60%**	**0.45**	**-30.26%**	**0**	**3.45%**	**0.25**	**-25.92%**	**1**	**17.62%**	**1.48**	**-7.75%**	**2**	**35.36%**	**2.63**	**-7.35%**

Table A.12 Performance statistics for 10-year bund futures

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-30 D & 2-100 D	15	0.16%	0.03	-12.31%	14	0.85%	0.19	-5.33%	17	-2.15%	-0.39	-5.33%	18	-2.07%	-0.52	-1.84%
5-50 D & 2-100 D	8	0.81%	0.16	-12.35%	6	2.30%	0.47	-4.87%	8	-0.66%	-0.11	-4.87%	6	4.02%	0.90	-2.05%
1-32 D / 1-61 D / 1-117D	16	-0.37%	-0.08	-12.16%	14	0.57%	0.12	-4.48%	17	-1.24%	-0.23	-4.48%	12	0.39%	0.10	-1.66%
Model Switch	9	1.26%	0.23	-12.34%	7	1.74%	0.32	-7.85%	11	-3.02%	-0.48	-7.85%	8	8.70%	1.77	-1.72%
Strategy #2	*MACD with No-trade volatility filter*															
1-30 D & 2-100 D	13	1.54%	0.42	-7.15%	11	2.94%	0.76	-3.14%	7	4.23%	1.07	-1.90%	12	-1.22%	-0.32	-6.64%
5-50 D & 2-100 D	9	0.99%	0.25	-10.85%	5	3.45%	0.83	-3.39%	6	2.45%	0.58	-3.39%	6	1.70%	0.39	-4.80%
1-32 D / 1-61 D / 1-117D	15	0.41%	0.11	-8.08%	12	2.23%	0.57	-4.35%	8	3.95%	1.00	-1.89%	10	0.22%	0.06	-6.02%
Model Switch	11	2.21%	0.50	-8.46%	8	3.58%	0.78	-4.39%	9	3.09%	0.71	-3.59%	10	5.13%	1.13	-6.64%
Strategy #3	*MACD with Reverse volatility filter*															
1-30 D & 2-100 D	20	2.36%	0.50	-7.02%	16	4.53%	1.00	-3.88%	21	9.16%	1.68	-1.84%	20	-1.19%	-0.30	-1.84%
5-50 D & 2-100 D	14	0.93%	0.18	-14.28%	9	4.39%	0.90	-4.43%	14	4.98%	0.85	-3.10%	8	-0.75%	-0.17	-2.22%
1-32 D / 1-61 D / 1-117D	22	0.69%	0.14	-9.55%	17	3.44%	0.75	-5.00%	22	7.86%	1.45	-1.92%	15	-0.42%	-0.10	-1.92%
Model Switch	18	2.86%	0.51	-10.48%	12	5.16%	0.96	-6.62%	18	8.50%	1.35	-2.77%	12	1.55%	0.31	-2.59%
Buy & Hold	**0**	**0.14%**	**0.03**	**-14.04%**	**0**	**2.12%**	**0.39**	**-7.50%**	**1**	**-0.36%**	**-0.06**	**-7.28%**	**2**	**1.25%**	**0.25**	**-3.54%**

Table A.13 Performance statistics for 30-year T-bond futures

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
40-100 D & 50-150 D	2	-0.30%	-0.03	-20.86%	2	-3.90%	-0.39	-20.86%	2	-10.43%	-0.99	-20.72%	4	4.87%	0.54	-5.73%
50-90 D & 40-100 D	3	1.12%	0.11	-17.90%	3	-2.13%	-0.19	-17.90%	4	-6.06%	-0.51	-17.90%	4	13.72%	1.28	-4.44%
1-32 D / 1-61 D / 1-117D	16	-1.20%	-0.14	-16.87%	18	-3.73%	-0.40	-16.87%	24	-8.69%	-0.84	-15.44%	28	-22.61%	-2.57	-12.41%
Model Switch	3	2.07%	0.20	-16.80%	3	-1.14%	-0.10	-16.80%	4	-3.51%	-0.28	-16.80%	4	17.94%	1.62	-3.73%
Strategy #2	*MACD with No-trade volatility filter*															
40-100 D & 50-150 D	4	1.43%	0.17	-15.19%	5	-1.08%	-0.12	-15.19%	3	-4.98%	-0.64	-14.10%	4	-1.11%	-0.16	-4.79%
50-90 D & 40-100 D	5	2.59%	0.28	-13.90%	6	0.25%	0.03	-13.90%	8	-1.82%	-0.20	-13.90%	6	10.04%	1.11	-3.73%
1-32 D / 1-61 D / 1-117D	16	-0.97%	-0.12	-13.70%	17	-3.35%	-0.39	-13.70%	20	-3.34%	-0.40	-7.30%	22	-14.23%	-1.73	-8.73%
Model Switch	5	3.47%	0.37	-12.14%	7	1.13%	0.11	-12.14%	8	-0.36%	-0.04	-12.14%	6	14.27%	1.50	-3.73%
Strategy #3	*MACD with Reverse volatility filter*															
40-100 D & 50-150 D	6	3.13%	0.34	-11.71%	8	1.68%	0.17	-11.71%	6	0.36%	0.03	-11.71%	6	-7.21%	-0.80	-6.13%
50-90 D & 40-100 D	8	4.00%	0.40	-13.55%	11	2.55%	0.23	-13.55%	14	2.29%	0.19	-13.55%	10	6.25%	0.58	-5.51%
1-32 D / 1-61 D / 1-117D	18	-0.90%	-0.10	-17.80%	22	-3.24%	-0.34	-17.80%	27	1.36%	0.13	-6.87%	29	-6.69%	-0.75	-8.30%
Model Switch	8	4.82%	0.47	-14.66%	11	3.33%	0.30	-14.66%	14	2.68%	0.22	-14.66%	10	10.47%	0.94	-5.51%
Buy & Hold	**0**	**1.42%**	**0.14**	**-18.48%**	**0**	**3.01%**	**0.27**	**-16.00%**	**1**	**-2.26%**	**-0.18**	**-16.00%**	**2**	**2.62%**	**0.24**	**-5.51%**

Table A.14 Performance statistics for brent oil futures

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
1-10 D & 2-5 D	44	8.30%	0.24	-45.54%	44	0.51%	0.02	-45.54%	43	15.63%	0.48	-21.77%	41	8.66%	0.32	-11.68%
1-32 D / 1-61 D / 1-117D	16	3.67%	0.12	-42.10%	17	-7.18%	-0.24	-42.10%	17	-10.08%	-0.33	-36.44%	26	-29.25%	-1.05	-29.03%
1-25 D & 2-5 D	37	13.66%	0.43	-37.25%	38	4.36%	0.15	-37.25%	39	8.33%	0.29	-14.99%	43	-15.74%	-0.61	-17.66%
Model Switch	48	8.01%	0.22	-55.19%	50	3.47%	0.10	-55.19%	43	22.08%	0.64	-20.50%	55	21.29%	0.69	-9.80%
Strategy #2	*MACD with No-trade volatility filter*															
1-10 D & 2-5 D	37	22.70%	0.79	-34.91%	38	15.24%	0.56	-28.18%	40	20.46%	0.71	-20.47%	41	8.66%	0.32	-11.68%
1-32 D / 1-61 D / 1-117D	15	14.58%	0.53	-42.10%	16	-6.78%	-0.26	-42.10%	18	-16.32%	-0.61	-36.44%	26	-29.25%	-1.05	-29.03%
1-25 D & 2-5 D	32	26.13%	0.97	-20.11%	33	13.90%	0.55	-17.66%	36	10.00%	0.39	-14.99%	43	-15.74%	-0.61	-17.66%
Model Switch	42	22.18%	0.71	-37.63%	45	20.41%	0.68	-28.22%	41	25.73%	0.84	-20.50%	55	21.29%	0.69	-9.80%
Strategy #3	*MACD with Reverse volatility filter*															
1-10 D & 2-5 D	49	34.94%	1.03	-30.89%	49	28.03%	0.88	-28.18%	45	24.37%	0.75	-20.47%	41	8.66%	0.32	-11.68%
1-32 D / 1-61 D / 1-117D	22	24.67%	0.78	-47.80%	21	-6.94%	-0.23	-47.80%	20	-22.64%	-0.74	-42.14%	26	-29.25%	-1.05	-29.03%
1-25 D & 2-5 D	42	36.81%	1.17	-20.54%	41	21.86%	0.73	-17.66%	41	10.73%	0.37	-14.99%	43	-15.74%	-0.61	-17.66%
Model Switch	53	34.38%	0.94	-37.63%	55	35.65%	1.02	-28.22%	45	28.68%	0.83	-20.50%	55	21.29%	0.69	-9.80%
Buy & Hold	**0**	**28.31%**	**0.77**	**-57.99%**	**0**	**15.39%**	**0.44**	**-47.99%**	**1**	**10.83%**	**0.31**	**-36.19%**	**2**	**36.33%**	**1.17**	**-13.50%**

Table A.15 Performance statistics for copper futures

	6-year Period (17/12/1998 - 30/03/2004)				*3-year Period (02/01/2001 - 30/03/2004)*				*Year 2003 (02/01/2003 - 31/12/2003)*				*Half Year (01/09/2003 - 30/03/2004)*			
	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD	Ann. Trades	Ann. Return	IR	Max. DD
Strategy #1	*MACD model without volatility filter*															
2-50 D & 5-100 D	7	12.49%	0.76	-22.65%	5	24.16%	1.47	-11.18%	6	27.02%	1.82	-11.18%	2	101.26%	4.74	-7.24%
1-100 D & 5-100 D	5	14.69%	0.83	-21.11%	4	24.84%	1.45	-13.64%	5	31.20%	2.00	-11.11%	2	101.26%	4.74	-7.24%
1-32 D / 1-61 D / 1-117D	15	7.75%	0.48	-35.82%	12	17.50%	1.11	-14.27%	12	21.06%	1.49	-11.49%	3	97.31%	4.60	-7.24%
Model Switch	6	11.21%	0.62	-27.85%	5	21.84%	1.26	-15.41%	5	29.86%	1.88	-13.11%	2	101.26%	4.74	-7.24%
Strategy #2	*MACD with No-trade volatility filter*															
2-50 D & 5-100 D	7	12.38%	0.79	-22.33%	5	23.96%	1.51	-11.18%	6	27.02%	1.82	-11.18%	4	99.91%	5.58	-6.36%
1-100 D & 5-100 D	6	14.57%	0.87	-21.11%	4	24.63%	1.49	-13.64%	5	31.20%	2.00	-11.11%	4	99.91%	5.58	-6.36%
1-30 D & 5-100 D	15	7.64%	0.50	-35.82%	13	17.30%	1.15	-14.27%	12	21.06%	1.49	-11.49%	5	95.96%	5.42	-5.75%
Model Switch	6	11.10%	0.64	-27.85%	6	21.63%	1.29	-15.41%	5	29.86%	1.88	-13.11%	4	99.91%	5.58	-6.36%
Strategy #3	*MACD with Reverse volatility filter*															
2-50 D & 5-100 D	8	12.27%	0.74	-22.05%	6	23.75%	1.44	-11.18%	6	27.02%	1.82	-11.18%	6	98.57%	4.61	-8.26%
1-100 D & 5-100 D	6	14.46%	0.82	-21.11%	5	24.43%	1.43	-13.64%	5	31.20%	2.00	-11.11%	6	98.57%	4.61	-8.26%
1-30 D & 5-100 D	16	7.53%	0.47	-35.82%	13	17.09%	1.08	-14.27%	12	21.06%	1.49	-11.49%	7	94.62%	4.46	-8.26%
Model Switch	7	10.98%	0.61	-27.85%	6	21.43%	1.23	-15.41%	5	29.86%	1.88	-13.11%	6	98.57%	4.61	-8.26%
Buy & Hold	**0**	**14.38%**	**0.80**	**-40.36%**	**0**	**16.18%**	**0.93**	**-30.31%**	**1**	**39.42%**	**2.49**	**-9.62%**	**2**	**101.26%**	**4.74**	**-7.24%**

Table A.16 GARCH model estimation output for EUR/USD

Dependent Variable: EURUSD
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 11:42
Sample: 1 1659
Included observations: 1659
Convergence achieved after 16 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.014692	0.014471	1.015263	0.3100
		Variance Equation		
C	0.003610	0.001673	2.157676	0.0310
ARCH(1)	0.022654	0.006041	3.750060	0.0002
GARCH(1)	0.968534	0.008747	110.7305	0.0000

R-squared	-0.000102	Mean dependent var	0.008418
Adjusted R-squared	-0.001915	S.D. dependent var	0.620534
S.E. of regression	0.621128	Akaike info criterion	1.859237
Sum squared resid	638.4993	Schwarz criterion	1.872290
Log likelihood	-1538.237	Durbin-Watson stat	1.937738

Table A.17 GARCH model estimation output for USD/JPY

Dependent Variable: USDJPY
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 11:54
Sample: 1 1659
Included observations: 1659
Convergence achieved after 13 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002096	0.016187	0.129455	0.8970
	Variance Equation			
C	0.007976	0.002015	3.959200	0.0001
ARCH(1)	0.049828	0.006824	7.301699	0.0000
GARCH(1)	0.934984	0.008933	104.6626	0.0000

R-squared	-0.000194	Mean dependent var	-0.008141
Adjusted R-squared	-0.002007	S.D. dependent var	0.735053
S.E. of regression	0.735790	Akaike info criterion	2.085608
Sum squared resid	895.9960	Schwarz criterion	2.098662
Log likelihood	-1726.012	Durbin-Watson stat	1.900225

Table A.18 GARCH model estimation output for GBP/USD

Dependent Variable: GBPUSD
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 11:50
Sample: 1 1659
Included observations: 1659
Convergence achieved after 10 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.012205	0.011193	1.090464	0.2755
		Variance Equation		
C	0.005117	0.001932	2.649036	0.0081
ARCH(1)	0.039903	0.009196	4.339034	0.0000
GARCH(1)	0.938807	0.015747	59.61978	0.0000

R-squared	-0.000080	Mean dependent var	0.007868
Adjusted R-squared	-0.001893	S.D. dependent var	0.484593
S.E. of regression	0.485052	Akaike info criterion	1.348308
Sum squared resid	389.3802	Schwarz criterion	1.361362
Log likelihood	-1114.422	Durbin-Watson stat	1.862527

Table A.19 GARCH model estimation output for USD/CHF

Dependent Variable: USDCHF
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 12:07
Sample: 1 1659
Included observations: 1659
Convergence achieved after 21 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.003354	0.016149	-0.207721	0.8354
		Variance Equation		
C	0.478594	0.014173	33.76918	0.0000
ARCH(1)	-0.005634	0.002031	-2.774527	0.0055
GARCH(1)	0.913917	0.002622	348.5323	0.0000
GARCH(2)	-0.992180	0.002369	-418.9016	0.0000

R-squared	-0.000034	Mean dependent var	-0.007247
Adjusted R-squared	-0.002453	S.D. dependent var	0.664055
S.E. of regression	0.664869	Akaike info criterion	2.013639
Sum squared resid	731.1523	Schwarz criterion	2.029956
Log likelihood	-1665.313	Durbin-Watson stat	1.982360

Table A.20 GARCH model estimation output for USD/CAD

Dependent Variable: USDCAD
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 12:05
Sample: 1 1659
Included observations: 1659
Convergence achieved after 12 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003474	0.008876	0.391397	0.6955
		Variance Equation		
C	0.001389	0.000576	2.411976	0.0159
ARCH(1)	0.042552	0.006733	6.320078	0.0000
GARCH(1)	0.949681	0.007995	118.7876	0.0000

R-squared	-0.000168	Mean dependent var	-0.001808
Adjusted R-squared	-0.001981	S.D. dependent var	0.408177
S.E. of regression	0.408581	Akaike info criterion	0.933531
Sum squared resid	276.2827	Schwarz criterion	0.946585
Log likelihood	-770.3643	Durbin-Watson stat	1.945313

Table A.21 GARCH model estimation output for AUD/USD

Dependent Variable: AUDUSD
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 11:57
Sample: 1 1659
Included observations: 1659
Convergence achieved after 12 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015460	0.016438	0.940483	0.3470
	Variance Equation			
C	0.006997	0.002315	3.022023	0.0025
ARCH(1)	0.038822	0.007068	5.492350	0.0000
GARCH(1)	0.947743	0.010105	93.78656	0.0000

R-squared	-0.000104	Mean dependent var	0.008182
Adjusted R-squared	-0.001917	S.D. dependent var	0.715163
S.E. of regression	0.715848	Akaike info criterion	2.107396
Sum squared resid	848.0843	Schwarz criterion	2.120450
Log likelihood	-1744.085	Durbin-Watson stat	1.938276

Table A.22 GARCH model estimation output for EUR/GBP

Dependent Variable: EURGBP
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 12:01
Sample: 1 1659
Included observations: 1659
Convergence achieved after 19 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004078	0.011239	0.362798	0.7168
	Variance Equation			
C	0.003280	0.001400	2.343666	0.0191
ARCH(1)	0.032052	0.007875	4.069948	0.0000
GARCH(1)	0.953563	0.011945	79.83118	0.0000

R-squared	-0.000026	Mean dependent var	0.001614
Adjusted R-squared	-0.001839	S.D. dependent var	0.479207
S.E. of regression	0.479647	Akaike info criterion	1.328838
Sum squared resid	380.7515	Schwarz criterion	1.341892
Log likelihood	-1098.271	Durbin-Watson stat	1.919548

Table A.23 GARCH model estimation output for EUR/JPY

Dependent Variable: EURJPY
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 12:02
Sample: 1 1659
Included observations: 1659
Convergence achieved after 18 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.021311	0.017818	1.196018	0.2317
	Variance Equation			
C	0.001753	0.000919	1.907767	0.0564
ARCH(1)	0.079456	0.022448	3.539551	0.0004
ARCH(2)	-0.059589	0.023109	-2.578622	0.0099
GARCH(1)	0.977428	0.004593	212.8259	0.0000

R-squared	-0.000719	Mean dependent var	-0.000408
Adjusted R-squared	-0.003139	S.D. dependent var	0.810099
S.E. of regression	0.811369	Akaike info criterion	2.325287
Sum squared resid	1088.862	Schwarz criterion	2.341604
Log likelihood	-1923.826	Durbin-Watson stat	1.863591

Table A.24 GARCH model estimation output for EUR/CHF

Dependent Variable: EURCHF
Method: ML - ARCH (Marquardt)
Date: 06/29/05 Time: 11:59
Sample: 1 1659
Included observations: 1659
Convergence achieved after 16 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001233	0.005126	0.240515	0.8099
		Variance Equation		
C	0.001962	0.000418	4.690314	0.0000
ARCH(1)	0.121778	0.015543	7.834886	0.0000
GARCH(1)	0.539250	0.163472	3.298735	0.0010
GARCH(2)	0.308072	0.148177	2.079084	0.0376
R-squared	-0.000199	Mean dependent var	-0.002026	
Adjusted R-squared	-0.002618	S.D. dependent var	0.231145	
S.E. of regression	0.231448	Akaike info criterion	-0.230381	
Sum squared resid	88.60147	Schwarz criterion	-0.214064	
Log likelihood	196.1009	Durbin-Watson stat	1.861126	

Table A.25 MS model estimation output for EUR/USD

LogL: EURUSDMS
Method: Maximum Likelihood (Marquardt)
Date: 06/09/05 Time: 22:18
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.40000, C(3)=0.00000, C(2)=0.30000,
C(5)=0.40000, C(4)=0.60000
Convergence achieved after 18 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.465461	0.018486	25.17883	0.0000
C(3)	0.006503	0.014770	0.440271	0.6597
C(2)	0.692390	0.015721	44.04244	0.0000
C(5)	4.957915	0.491121	10.09511	0.0000
C(4)	4.379202	0.467438	9.368526	0.0000

Log likelihood	-1531.475	Akaike info criterion	1.852291
Avg. log likelihood	-0.923132	Schwarz criterion	1.868608
Number of Coefs.	5	Hannan-Quinn criter.	1.858339

Table A.26 MS model estimation output for USD/JPY

LogL: USDJPYMS
Method: Maximum Likelihood (Marquardt)
Date: 06/09/05 Time: 22:39
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000,
C(5)=0.20000, C(4)=0.80000
Convergence achieved after 36 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.460411	0.064999	22.46831	0.0000
C(3)	0.006338	0.016135	0.392786	0.6945
C(2)	0.594996	0.012696	46.86401	0.0000
C(5)	4.207500	0.305246	13.78398	0.0000
C(4)	1.937530	0.328712	5.894309	0.0000

Log likelihood	-1716.587	Akaike info criterion	2.075452
Avg. log likelihood	-1.034712	Schwarz criterion	2.091769
Number of Coefs.	5	Hannan-Quinn criter.	2.081500

Table A.27 MS model estimation output for GBP/USD

LogL: GBPUSDMS
Method: Maximum Likelihood (Marquardt)
Date: 06/09/05 Time: 22:41
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000,
C(5)=0.20000, C(4)=0.80000
Convergence achieved after 22 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.602187	0.020267	29.71314	0.0000
C(3)	0.007858	0.011250	0.698523	0.4848
C(2)	0.381519	0.012803	29.79826	0.0000
C(5)	3.888702	0.395877	9.823000	0.0000
C(4)	3.542546	0.383915	9.227433	0.0000

Log likelihood	-1111.636	Akaike info criterion	1.346156
Avg. log likelihood	-0.670064	Schwarz criterion	1.362473
Number of Coefs.	5	Hannan-Quinn criter.	1.352204

Table A.28 MS model estimation output for USD/CHF

LogL: USDCHFMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:24
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.40000, C(3)=0.00000, C(2)=0.30000,
C(5)=0.40000, C(4)=0.60000
Convergence achieved after 32 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.501763	0.023581	21.27849	0.0000
C(3)	-0.002260	0.015651	-0.144426	0.8852
C(2)	0.737183	0.019347	38.10382	0.0000
C(5)	4.496765	0.477744	9.412493	0.0000
C(4)	3.873535	0.493800	7.844348	0.0000

Log likelihood	-1654.024	Akaike info criterion	2.000029
Avg. log likelihood	-0.997001	Schwarz criterion	2.016346
Number of Coefs.	5	Hannan-Quinn criter.	2.006077

Table A.29 MS model estimation output for USD/CAD

LogL: USDCADMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:26
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000,
C(5)=0.20000, C(4)=0.80000
Convergence achieved after 13 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.580034	0.021362	27.15228	0.0000
C(3)	0.001365	0.008845	0.154324	0.8774
C(2)	0.319720	0.007026	45.50576	0.0000
C(5)	5.283828	0.457886	11.53961	0.0000
C(4)	4.373056	0.435604	10.03905	0.0000

Log likelihood	-765.6142	Akaike info criterion	0.929011
Avg. log likelihood	-0.461491	Schwarz criterion	0.945328
Number of Coefs.	5	Hannan-Quinn criter.	0.935059

Table A.30 MS model estimation output for AUD/USD

LogL: AUDUSDMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:28
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000,
C(5)=0.20000, C(4)=0.80000
Convergence achieved after 80 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.913639	0.019000	48.08510	0.0000
C(3)	0.019584	0.016310	1.200727	0.2299
C(2)	0.568263	0.013630	41.69116	0.0000
C(5)	4.804987	0.418926	11.46978	0.0000
C(4)	4.400473	0.427572	10.29178	0.0000

Log likelihood	-1735.974	Akaike info criterion	2.098823
Avg. log likelihood	-1.046398	Schwarz criterion	2.115140
Number of Coefs.	5	Hannan-Quinn criter.	2.104871

Table A.31 MS model estimation output for EUR/GBP

LogL: EURGBPMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:30
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000, C(5)=0.20000, C(4)=0.80000
Convergence achieved after 13 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.575673	0.019024	30.26033	0.0000
C(3)	-0.003484	0.011029	-0.315865	0.7521
C(2)	0.355347	0.013732	25.87702	0.0000
C(5)	3.599420	0.378195	9.517375	0.0000
C(4)	3.619656	0.374510	9.665034	0.0000

Log likelihood	-1091.953	Akaike info criterion	1.322427
Avg. log likelihood	-0.658200	Schwarz criterion	1.338744
Number of Coefs.	5	Hannan-Quinn criter.	1.328475

Table A.32 MS model estimation output for EUR/JPY

LogL: EURJPYMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:31
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.60000, C(3)=0.00000, C(2)=0.20000, C(5)=0.20000, C(4)=0.80000
Convergence achieved after 28 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	1.185628	0.040567	29.22672	0.0000
C(3)	0.011680	0.017657	0.661477	0.5083
C(2)	0.611180	0.017024	35.90005	0.0000
C(5)	3.613068	0.298489	12.10453	0.0000
C(4)	2.590070	0.290974	8.901394	0.0000

Log likelihood	-1914.740	Akaike info criterion	2.314334
Avg. log likelihood	-1.154153	Schwarz criterion	2.330651
Number of Coefs.	5	Hannan-Quinn criter.	2.320382

Table A.33 MS model estimation output for EUR/CHF

LogL: EURCHFMS
Method: Maximum Likelihood (Marquardt)
Date: 06/10/05 Time: 11:34
Sample: 1 1659
Included observations: 1659
Evaluation order: By observation
Estimation settings: tol= 1.0E-05, derivs=accurate numeric
Initial Values: C(1)=0.30000, C(3)=0.00000, C(2)=0.10000, C(5)=0.20000, C(4)=0.80000
Convergence achieved after 23 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.321018	0.005519	58.17121	0.0000
C(3)	-0.000233	0.004678	-0.049740	0.9603
C(2)	0.148521	0.004165	35.65636	0.0000
C(5)	3.471758	0.263559	13.17260	0.0000
C(4)	2.976897	0.251599	11.83193	0.0000

Log likelihood	221.0632	Akaike info criterion	-0.260474
Avg. log likelihood	0.133251	Schwarz criterion	-0.244157
Number of Coefs.	5	Hannan-Quinn criter.	-0.254426

Table A.34 Test output on the presence of a deterministic trend for EUR/USD

Dependent Variable: EURUSD
Method: Least Squares
Date: 02/08/06 Time: 22:41
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	116.9671	0.385366	303.5222	0.0000
TREND	-0.002695	0.000402	-6.710396	0.0000

R-squared	0.026394	Mean dependent var	114.7279
Adjusted R-squared	0.025808	S.D. dependent var	7.964580
S.E. of regression	7.861132	Akaike info criterion	6.962940
Sum squared resid	102645.5	Schwarz criterion	6.969454
Log likelihood	-5787.685	F-statistic	45.02942
Durbin-Watson stat	0.008409	Prob(F-statistic)	0.000000

Table A.35 Test output on the presence of a deterministic trend for USD/JPY

Dependent Variable: USDJPY
Method: Least Squares
Date: 02/08/06 Time: 22:42
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.445805	0.005733	252.1728	0.0000
TREND	0.000197	5.97E-06	33.04157	0.0000

R-squared	0.396602	Mean dependent var	1.609840
Adjusted R-squared	0.396239	S.D. dependent var	0.150519
S.E. of regression	0.116956	Akaike info criterion	-1.452832
Sum squared resid	22.72041	Schwarz criterion	-1.446318
Log likelihood	1210.030	F-statistic	1091.746
Durbin-Watson stat	0.004813	Prob(F-statistic)	0.000000

Table A.36 Test output on the presence of a deterministic trend for GBP/USD

Dependent Variable: GBPUSD
Method: Least Squares
Date: 02/08/06 Time: 22:41
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.888257	0.005343	166.2535	0.0000
TREND	0.000197	5.57E-06	35.32667	0.0000

R-squared	0.429008	Mean dependent var	1.051689
Adjusted R-squared	0.428664	S.D. dependent var	0.144190
S.E. of regression	0.108988	Akaike info criterion	-1.593950
Sum squared resid	19.73011	Schwarz criterion	-1.587436
Log likelihood	1327.370	F-statistic	1247.973
Durbin-Watson stat	0.003615	Prob(F-statistic)	0.000000

Table A.37 Test output on the presence of a deterministic trend for USD/CHF

Dependent Variable: USDCHF
Method: Least Squares
Date: 02/08/06 Time: 22:42
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.723203	0.006191	278.3591	0.0000
TREND	-0.000288	6.45E-06	-44.64288	0.0000

R-squared	0.545428	Mean dependent var	1.483900
Adjusted R-squared	0.545154	S.D. dependent var	0.187245
S.E. of regression	0.126282	Akaike info criterion	-1.299390
Sum squared resid	26.48839	Schwarz criterion	-1.292876
Log likelihood	1082.443	F-statistic	1992.986
Durbin-Watson stat	0.006116	Prob(F-statistic)	0.000000

Table A.38 Test output on the presence of a deterministic trend for USD/CAD

Dependent Variable: USDCAD
Method: Least Squares
Date: 02/08/06 Time: 22:42
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.579868	0.004152	380.5146	0.0000
TREND	-0.000156	4.33E-06	-36.04861	0.0000

R-squared	0.438947	Mean dependent var	1.450268
Adjusted R-squared	0.438609	S.D. dependent var	0.113039
S.E. of regression	0.084696	Akaike info criterion	-2.098302
Sum squared resid	11.91495	Schwarz criterion	-2.091788
Log likelihood	1746.738	F-statistic	1299.502
Durbin-Watson stat	0.005296	Prob(F-statistic)	0.000000

Table A.39 Test output on the presence of a deterministic trend for AUD/USD

Dependent Variable: AUDUSD
Method: Least Squares
Date: 02/08/06 Time: 22:39
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.542951	0.003599	150.8476	0.0000
TREND	9.70E-05	3.75E-06	25.86298	0.0000

R-squared	0.287092	Mean dependent var	0.623557
Adjusted R-squared	0.286663	S.D. dependent var	0.086933
S.E. of regression	0.073423	Akaike info criterion	-2.383946
Sum squared resid	8.954441	Schwarz criterion	-2.377432
Log likelihood	1984.251	F-statistic	668.8939
Durbin-Watson stat	0.003452	Prob(F-statistic)	0.000000

Table A.40 Test output on the presence of a deterministic trend for EUR/GBP

Dependent Variable: EURGBP
Method: Least Squares
Date: 02/08/06 Time: 22:40
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.617579	0.001388	444.9140	0.0000
TREND	4.01E-05	1.45E-06	27.75129	0.0000

R-squared	0.316780	Mean dependent var	0.650934
Adjusted R-squared	0.316368	S.D. dependent var	0.034247
S.E. of regression	0.028316	Akaike info criterion	-4.289593
Sum squared resid	1.331762	Schwarz criterion	-4.283079
Log likelihood	3568.797	F-statistic	770.1343
Durbin-Watson stat	0.011044	Prob(F-statistic)	0.000000

Table A.41 Test output on the presence of a deterministic trend for EUR/JPY

Dependent Variable: EURJPY
Method: Least Squares
Date: 02/08/06 Time: 22:41
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	104.6849	0.494814	211.5640	0.0000
TREND	0.018473	0.000516	35.82894	0.0000

R-squared	0.435938	Mean dependent var	120.0361
Adjusted R-squared	0.435599	S.D. dependent var	13.43569
S.E. of regression	10.09379	Akaike info criterion	7.462919
Sum squared resid	169230.2	Schwarz criterion	7.469433
Log likelihood	-6203.417	F-statistic	1283.713
Durbin-Watson stat	0.007128	Prob(F-statistic)	0.000000

Table A.42 Test output on the presence of a deterministic trend for EUR/CHF

Dependent Variable: EURCHF
Method: Least Squares
Date: 02/08/06 Time: 22:39
Sample: 1 1663
Included observations: 1663

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.565084	0.002114	740.3810	0.0000
TREND	-3.70E-05	2.20E-06	-16.78147	0.0000

R-squared	0.144968	Mean dependent var	1.534367
Adjusted R-squared	0.144453	S.D. dependent var	0.046620
S.E. of regression	0.043122	Akaike info criterion	-3.448385
Sum squared resid	3.088578	Schwarz criterion	-3.441871
Log likelihood	2869.332	F-statistic	281.6177
Durbin-Watson stat	0.006095	Prob(F-statistic)	0.000000

Table A.43 Portfolio performance statistics without volatility filters after transaction costs

	CONSTRAINED AGAINST SHORT SELLING				UNCONSTRAINED			
	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04
RAER								
Annualised Return	4.89%	1.78%	7.33%	5.55%	6.55%	4.23%	16.43%	-0.98%
Annualised Volatility	9.00%	8.61%	10.42%	7.78%	15.75%	13.57%	18.97%	14.12%
Information Ratio	0.54	0.21	0.70	0.71	0.42	0.31	0.87	-0.07
Maximum Drawdown	-26.63%	-26.63%	-12.62%	-7.88%	-37.23%	-21.59%	-28.18%	-21.69%
Historical Mean								
Annualised Return	-13.96%	-16.95%	-16.27%	-8.69%	-44.20%	-47.47%	-45.83%	-39.31%
Annualised Volatility	12.62%	10.38%	13.57%	13.65%	17.92%	14.91%	18.81%	19.74%
Information Ratio	-1.11	-1.63	-1.20	-0.64	-2.47	-3.18	-2.44	-1.99
Maximum Drawdown	-208.38%	-78.83%	-71.76%	-65.02%	-580.14%	-205.52%	-198.55%	-177.22%
Minimun Variance								
Annualised Return	0.37%	-0.28%	-0.05%	1.43%	-0.27%	-1.15%	-0.80%	1.15%
Annualised Volatility	3.69%	3.94%	3.64%	3.48%	3.72%	3.97%	3.65%	3.53%
Information Ratio	0.10	-0.07	-0.01	0.41	-0.07	-0.29	-0.22	0.32
Maximum Drawdown	-11.94%	-11.94%	-7.02%	-5.25%	-16.93%	-14.94%	-8.16%	-5.88%
Rollover								
Annualised Return	2.19%	1.93%	6.31%	-1.65%	-0.19%	2.33%	2.87%	-5.75%
Annualised Volatility	9.71%	9.16%	10.43%	9.50%	16.85%	15.71%	20.13%	14.18%
Information Ratio	0.23	0.21	0.61	-0.17	-0.01	0.15	0.14	-0.41
Maximum Drawdown	-31.39%	-12.54%	-10.83%	-31.39%	-62.15%	-27.88%	-39.12%	-41.84%
Equally Weighted								
Annualised Return	5.26%	7.01%	8.05%	0.74%				
Annualised Volatility	9.46%	7.79%	9.43%	10.91%				
Information Ratio	0.56	0.90	0.85	0.07				
Maximum Drawdown	-37.02%	-8.62%	-11.03%	-36.97%				

Table A.44 Portfolio performances statistics with volatility filters after transaction costs

	CONSTRAINED AGAINST SHORT SELLING				UNCONSTRAINED			
	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04	01/01/92 29/12/04	01/01/92 24/04/96	01/05/96 23/08/00	30/08/00 29/12/04
RAER								
Annualised Return	10.13%	11.89%	13.38%	5.15%	10.29%	1.56%	18.52%	10.79%
Annualised Volatility	9.52%	9.83%	10.97%	7.44%	16.66%	13.57%	22.05%	12.75%
Information Ratio	1.06	1.21	1.22	0.69	0.62	0.11	0.84	0.85
Maximum Drawdown	-13.32%	-8.77%	-8.79%	-13.32%	-39.77%	-39.37%	-39.77%	-14.19%
Historical Mean								
Annualised Return	6.20%	8.57%	-0.06%	10.08%	-3.26%	-3.07%	-16.38%	9.60%
Annualised Volatility	16.73%	21.25%	14.36%	13.55%	17.58%	21.47%	14.82%	15.60%
Information Ratio	0.37	0.40	0.00	0.74	-0.19	-0.14	-1.11	0.62
Maximum Drawdown	-43.04%	-35.51%	-43.04%	-22.29%	-128.21%	-45.13%	-89.92%	-18.63%
Minimun Variance								
Annualised Return	0.45%	-0.50%	0.15%	1.70%	0.19%	-1.34%	0.18%	1.72%
Annualised Volatility	3.68%	3.92%	3.63%	3.49%	3.78%	4.10%	3.71%	3.49%
Information Ratio	0.12	-0.13	0.04	0.49	0.05	-0.33	0.05	0.49
Maximum Drawdown	-12.15%	-12.15%	-6.35%	-4.81%	-13.76%	-13.76%	-6.81%	-4.81%
Rollover								
Annualised Return	9.84%	11.95%	14.49%	3.09%	7.67%	-1.16%	19.46%	4.71%
Annualised Volatility	9.06%	9.91%	11.17%	4.81%	19.17%	26.69%	18.76%	6.19%
Information Ratio	1.08	1.21	1.30	0.64	0.40	-0.04	1.04	0.76
Maximum Drawdown	-8.90%	-8.82%	-8.90%	-6.56%	-84.41%	-84.41%	-24.83%	-7.40%
Equally Weighted								
Annualised Return	5.26%	7.01%	8.05%	0.74%				
Annualised Volatility	9.46%	7.79%	9.43%	10.91%				
Information Ratio	0.56	0.90	0.85	0.07				
Maximum Drawdown	-37.02%	-8.62%	-11.03%	-36.97%				

References

Akgiray, V. (1989), "Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecasts", *Journal of Business*, **62**, 55-80.

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

Andersen, T. G., Bollerslev, T. and Lange, S. (1999), "Forecasting Financial Market Volatility: Sample Frequency vis-à-vis Forecast Horizon", *Journal of Empirical Finance,* **6**, 457-477.

Bank of International Settlement (2004), *BIS Triennal Central Bank Survey 2004*, www.bis.org, September.

Bauer, R., Haerden, R. and Molenaar, R. (2004), "Asset Allocation in Stable and Unstable Times", *The Journal of Investing*, **Fall**, 72-80.

Bentz, Y. (2003), "Quantitative Equity Investment Management with Time-Varying Factor Sensitivities", pp.213-237, in *Applied Quantitative Methods for Trading and Investment* edited by C. L. Dunis, J. Laws and P. Naim, John Wiley & Sons, Chichester.

Best, M. J. and Grauer, R. R. (1991), "On the sensitivity of mean-variance-efficient portfolios to changes in asset means: some analytical and computational results", *Review of Financial Studies*, **4**, 315-342

Billingsley, R. and Chance, D. (1996), "Benefits and Limitations of

Diversification among Commodity Trading Advisors", *The Journal of Portfolio Management*, **Fall**, 65-80.

Billio, M. and Sartore, D. (2003), "Stochastic Volatility Models: A Survey with Applications to Option Pricing and Value at Risk", pp.239-291, in *Applied Quantitative Methods for Trading and Investment* edited by C. L. Dunis, J. Laws and P. Naim, John Wiley & Sons, Chichester.

Bilson, J. F. O. (1981), "The 'Speculative Efficiency' Hypothesis", *Journal of Business*, **54**, 435-451.

Blume, L., Easley, D. and O'Hara, M. (1994), "Market Statistics and Technical Analysis: The Role of Volume", *Journal of Finance*, **49**, 153-181.

Bollerslev, T. (1986), "Generalised Autoregressive Conditional Heteroskedasticity", *Journal of Econometrics*, **31**, 307-27.

Bollerslev, T., Chou, R. Y. and Kroner, K. F. (1992), "ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence", *Journal of Econometrics*, **52**, 5-59.

Breidt, F. J., Crato, N. and de Lima, P. (1998), "On the Detection and Estimation of Long Memory in Stochastic Volatility", *Journal of Econometrics*, **83**, 325-348

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

Caporale, G. M. and Spagnolo, N. (2004), "Modelling East Asian Exchange Rates: A Markov-switching Approach", *Applied Financial Economics*, **14**, 233-242.

Chatfield, C. (1994), *The Analysis of Time Series: An Introduction*, Chapman and Hall, London.

Chiarella, C., He, T. and Hommes, C. (2005), "A Dynamic Analysis of Moving Average Rules", *Tinbergen Institute Discussion Paper*, **TI 2005-057/1**.

Chong, C. W., Ahmad, M. I. and Abdullah, M. Y. (1999), "Performance of Garch Models in Forecasting Stock Market Volatility", *Journal of Forecasting*, **18**, 333-343.

Chow, G., Jacquier, E., Kritzman, M. and Lowry, K. (1999), "Optimal Portfolios in Good Times and Bad", *Financial Analyst Journal*, **55**, 72-80.

Clarida, R. H. and Taylor, M. P. (1997), "The Term Structure of Forward Exchange Premiums and the Forecastability of Spot Exchange Rates: Correcting the Errors", *Review of Economics and Statistics*, **89**, 353-361.

Clarida, R. H., Sarno, L., Taylor, M. P. and Valente, G. (2003), "The Out-of-Sample Success of Term Structure Models as Exchange Rate Predictors: A Step Beyond", *Journal of International Economics*, **60**, 61-83.

Douglas Van Eaton, R. and Conover, J. (2002), "Equity Allocations and the Investment Horizon: A Total Portfolio Approach", *Financial Service Review*, **11**, 117-133.

Dunis, C. and Chen, Y. X. (2005), "Alternative Volatility Models for Risk Management and Trading: An Application to the EUR/USD and USD/JPY Rates", *Derivatives Use, Trading & Regulation*, **11**, 126-156.

Dunis, C. and Miao, J. (2006), "Trading Foreign Exchange Portfolios with Volatility Filters: The Carry Model Revisited", *Applied Financial Economics*, **forthcoming**.

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.

Ehlers, J. (1999), "Cycle Tutorial", available at www.mesasoftware.com.

Engle, C. and Hamilton, J. D. (1990), "Long Swings in the Dollar: Are They in the Data and Do Markets Know It?", *American Economic Review*, **80**, 689-713.

Engel, R. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variances of U.K. Inflation", *Econometrica*, **50**, 987-1008.

Erb, C. B., Harvey, C. R. and Viskanta, T. E. (1994), "Forecasting International Correlation", *Financial Analyst Journal*, **50**, 32-45.

Fama, E. and Blume, M. (1966), "Filter Tests and Stock Market Trading", *Journal of Business*, **39**, 226-241.

Frenkel, J. A. (1976), "A Monetary Approach to the Exchange Rate: Doctrinal Aspects and Empirical Evidence", *Scandinavian Journal of Economics*, **78**, 200-224.

Frankel, J. A. (1980), "Tests of Rational Expectations in the Forward Exchange Market", *Southern Economic Journal*, **46**, 1083-1101.

Frenkel, J. A. and Johnson, H. G. [eds.] (1978), *The Economics of Exchange*

Rates: Selected Studies, Addison-Wesley, Reading, Massachusetts.

Gulko, L. (2002), "Decoupling", *Journal of Portfolio Management*, **Spring**, 59-66.

Hamilton, J. D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and Business Cycle", *Econometrica,* **57**, 357-384.

Hamilton, J. D. (1994), *Time Series Analysis*, Princeton University Press, Princeton.

Hurst, J. M. (1997), *Profit Magic of Stock Transaction Timing,* Traders Press, Greenville, South Carolina.

Jensen, G. (2003), "Hedge Funds Selling Betas as Alpha", *Bridgewater Daily Observations*, **June,** 1-6.

Jobson, J. D. and Korkie, B. (1981), "Putting Markowitz Theory to Work", *Journal of Portfolio Management*, **Summer**, 153-181.

JP Morgan (1994), *RiskMetrics Technical Document*, Morgan Guaranty Trust Company, New York.

Judge, G. G., Griffith, W. E., Hill, R. C., Lütkepohl, H. and Lee, T. -C. (1985), *The Theory and Practice of Econometrics*, 2nd edition, John Wiley & Sons, New York.

Kaufman, P. (1998), *Trading Systems and Methods,* John Wiley & Sons, New York.

Kwon, K. and Kish, R. (2002), "Technical Trading Strategies and Return Predictability: NYSE", *Applied Financial Economics*, **12**, 639-653.

LeBaron, B. (1991), "Technical Trading Rules and Regime Shifts in Foreign Exchange", *University of Wisconsin, Social Science Research, Working Paper*, **9118**.

LeBaron, B. (1992), "Do Moving Average Trading Rule Results Imply Nonlinearities in Foreign Exchange Markets?", *University of Wisconsin, Social Science Research, Working Paper*, **9222**.

Lequeux, P. and Acar, E. (1998), "A Dynamic Index for Managed Currencies Funds using CME Currency Contracts", *European Journal of Finance*, **4**, 311-330.

Leung, M. T., Daouk, H. and Chen, A. S. (2000), "Forecasting Stock Indices: a Comparison of Classification and Level Estimation Models", *International Journal of Forecasting*, **16**, 173-190.

Longin, F., and Solnik, B. (2001), "Extreme Correlation of International Equity Markets", *Journal of Finance*, **Apr**, 649-676.

Low, A. and Muthuswamy, J. (1996) "Information Flows in High Frequency Data" in C. L. Dunis [eds.], *Forecasting Financial Markets; Exchange Rates, Interest Rates and Asset Management*, 3-32, John Wiley & Sons, Chichester.

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

Meese, R. and Rogoff, K. (1983a), "Empirical Exchange Rate Models of the Seventies: Do They Fit out of Sample?", *Journal of International Economics*, **14**, 3-24.

Meese, R. and Rogoff, K. (1983b), "The Out-of-Sample Failure of Exchange Rate Models: Sampling Error or Misspecification?", in J. Frenkel [ed.]

Exchange Rates and International Macroeconomics, 67-105, University of Chicago Press, Chicago.

Mian, G. M. and Adam, C. M. (2001), "Volatility Dynamics in High Frequency Financial Data: an Empirical Investigation of the Australian Equity Returns", *Applied Financial Economics,* **11**, 341-352.

Miao, J. and Dunis, C. (2005), "Volatility Filters for Dynamic Portfolio Optimization", *Applied Financial Economic Letters*, **1**, 111-119.

Michaud, R. O. (1989), "The Markowitz Optimisation Enigma: Is 'Optimised' Optimal?", *Financial Analyst Journal,* **Jan-Feb**, 31-42.

Pagan, A. and Schwert, G. (1990), "Alternative Models for Conditional Stock Volatility", *Journal of Econometrics*, **45**, 267-290.

Pan, M. S., Liu. Y. and Roth, H. J. (2003), "Volatility and Trading Demands in Stock Index Futures", *Journal of Futures Markets*, **23**, 39-54.

Pesaran, M. H. and Timmermann, A. (1995), "Predictability of Stock Returns: Robustness and Economic Significance", *Journal of Finance,* **Sep**, 1201-1228.

Psychoyios, D., Skiadopoulos, G. and Alexakis, P. (2003), "A Review of Stochastic Volatility Processes: Properties and Implications", *The Journal of Risk Finance*, **Spring**, 43-59.

Ramchmand, L. and Susmel, R. (1998), "Volatility and Cross Correlation across Major Stock Markets", *Journal of Empirical Finance*, **5**, 397-416.

Ready, M. J. (2002), "Profits from Technical Trading Rules", *Financial*

Management, **Autumn**, 43-61.

Roche, B. B. and Rockinger, M. (2003), "Switching Regime Volatility: An Empirical Evaluation", in C. L. Dunis, J. Laws and P. Naim [eds.], *Applied Quantitative Methods for Trading and Investment*, 193-211, John Wiley & Sons, Chichester.

Solnik, B., Bourcrelle, C. and Le Fur, Y. (1996), "International Market Correlation and Volatility", *Financial Analyst Journal*, **52**, 17-34.

Sullivan, R., Timmerman, A. and White, H. (1999), "Data-snooping, Technical Trading Rule Performance, and the Bootstrap", *Journal of Finance,* **54**, 1647-1691.

Taylor, M. P. (1995), "The Economics of Exchange Rates", *Journal of Economic Literature*, **33**, 13-47.

Taylor, S. J. (1994), "Modelling Stochastic Volatility: a Review and Comparative Study", *Mathematical Finance*, **4**, 183-204.

Terui, N. and van Dijk, H. K. (2002), "Combined Forecasts from Linear and Nonlinear Time Series Models", *International Journal of Forecasting,* **18**, 421-438.

West, K. D. and Cho, D. (1995), "The Predictive Ability of Several Models of Exchange Rate Volatility", *Journal of Econometrics*, **69**, 367-391.

Wolff, C. P. (2000), "Forward Foreign Exchange Rates and Expected Future Spot Rates", *Applied Financial Economics*, **10**, 371-377.