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TRADING

FOREIGN EXCHANGE

CARRY PORTFOLIOS

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List of Abbreviations

AUD	Australian Dollar
BIS	Bank of International Settlements
CAD	Canadian Dollar
CHF	Swiss Franc
CIP	Covered Interest Rate Parity
CME	Chicago Mercantile Exchange
CTA	Commodity Trading Advisor
e.g.	*exempli gratia* (Latin for 'for example')
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Fund
EUR	Euro
FRUH	Forward Rate Unbiasedness Hypothesis
FX	Foreign Exchange
G10	Currency Universe defined in Section 2.2
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GBP	British Pound Sterling
i.e.	*id est* (Latin for 'that is')
JPY	Japanese Yen

LSH	Limits to Speculation Hypothesis
MACD	Moving Average Convergence Divergence Indicator
MPT	Modern Portfolio Theory
NOK	Norwegian Krone
NZD	New Zealand Dollar
OTC	Over the Counter
PHLX	Philadelphia Stock Exchange
RE	Rational Expectations
s.t.	*such that*
SEK	Swedish Krona
UIP	Uncovered Interest Rate Parity
USD	U.S. Dollar
VCV	Variance-Covariance Matrix

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Declaration

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Abstract

Foreign exchange carry trades involve buying high yielding currencies while selling low yielding currencies. Contrary to the implications of the uncovered interest parity condition, carry trades have generated consistent profits in the past decades. As foreign exchange has gained increased relevance as an asset class in its own, the carry trade emerged as a major driver of foreign exchange market turnover. Given the widespread use and ease of implementation of carry strategies, active currency managers should be evaluated relative to a benchmark which incorporates a proxy for carry trade returns.

Within this thesis we study the profitability of various carry portfolio strategies on a very recent data set ranging from the 1st of January 1999 to the 5th of March 2010. Within three distinct empirical chapters we analyse whether different asset allocation, market-timing and money management methodologies have the potential to improve the performance of a simple carry portfolio, such as the one implemented by the *Currency Harvest* exchange traded fund by Deutsche Bank.

Three main findings emerge from our investigation on carry trade portfolios.

First, we find that a simple carry trade proxy is difficult to outperform with asset allocation and market-timing techniques. Nevertheless, we would not conclude that professional currency managers should cease to implement carry strategies, since they can add value to the investment process by successfully addressing the issue of optimal leveraging for carry trades.

Second, we find that the portfolio flows of carry traders do uncover pockets of predictability in the FX market. Strategies which aim at front-running the trades of carry strategies, do generate positive returns with low correlations to traditional carry trade strategies and therefore offer good diversification vehicles for carry portfolios.

Lastly, we find that while profitable market-timing seems feasible on historical backtests, the results are strongly dependent on the correctly timing the credit crisis. Thus, we note that our results are affected by a lookback bias. We posit that before the credit crisis, portfolio managers would not have had the foresight to select the correct market-timing indicators. We thus advocate a broad diversification of risk indicators for carry trade timing.

Chapter 1

Introduction

The foreign exchange (FX) market runs 24 hours a day and with a daily turnover in excess of USD 3trn it constitutes the largest financial market in the world (see Borio et al. [2007]). The main financial instruments for trading currencies are swaps, spot transactions, forwards and options. Currencies are traded in an interbank exchange system by market making currency traders. The main participants in the FX market are central banks, commercial banks, institutional investors, traders, hedge funds, commercial companies and retail investors. The objectives pursued by these participants in the FX market range from pure profit generation (hegde funds, financial institutions) to hedging cash flows from business core activities (corporations) to implementing macroeconomic and monetary policy objectives (central banks).

According to Borio et al. [2007], the foreign exchange transaction volume more than doubled between April 2004 and April 2007. This increase of trading activity is attributed mainly to the growing importance of FX as an asset class. Pojarliev and Levich [2008] found that the bulk of managed FX returns can be explained by the returns to the four FX investment-styles *carry*, *momentum*, *valuation* and *volatility*. Since these investment-styles can be implemented systematically or even through the purchase of special exchange traded funds (ETFs), the generation of returns associated to these known factors does not require any particular skill. Pojarliev and Levich [2008] concluded that the returns inherent to these trading-styles should replace the riskless interest rate as the benchmark for professional FX managers, since simple replication of these popular return factors should not entitle to an extraordinary remuneration.

Within this thesis we will focus on the FX carry investment-style, which -

given its profitability over the past two decades, the thorough media coverage and the rising amount of academic publications - arguably denotes the most popular strategy for trading currencies. An FX carry trade involves buying a high yielding currency while selling a low yielding currency. The uncovered interest parity condition (UIP) states that exchange rate fluctuations should offset the interest rate differential earned on a cross currency position. Thus, the profitability of FX carry trades has been facilitated by the empirical failure of the uncovered interest rate parity condition.

Within our empirical research we will investigate on how different asset allocation, market-timing and money management methodologies affect the performance of currency portfolios implementing the carry investment-style. Thereby, we explore whether a simple proxy for carry trade returns can be outperformed by the application of such methodologies, thus justifying the deployment of advanced FX carry trade strategies by professional FX managers. We believe that our analyses of FX carry trade strategies from a portfolio managers perspective are essential to better understand current FX market dynamics, since the FX carry trade has been recognised a major driver of FX market turnover (see Galati et al. [2007a]).

In Chapter 4 of this thesis we will focus on testing different asset allocation techniques for FX carry portfolios. We will test the performance of three sets of currency portfolios related to the FX carry theme. With the first set of currency portfolios we compare the performance of simple equally weighted asset allocation algorithms versus mean-variance optimised asset allocation algorithms for setting up FX carry portfolios. Second, we will allocate capital to currencies based on different yield maturities in order to test whether the maturity of yields has a significant impact on carry trade returns. The third set of currency portfolios analysed in Chapter 4 will allocate capital to currencies according to how their attractiveness from an FX carry trading perspective has changed. Thus, this third set of currency portfolios mimics the likely portfolio flows generated by carry traders. We find that the portfolio positions to these *'carry-flows'* currency portfolios point out to pockets of predictability in foreign exchange rates fluctuations.

Recent literature on the carry trade has found significant relationships between FX carry trade returns and proxies for global volatility and liquidity (see

Section 3.3.4). Dunis and Miao [2007] analysed volatility-based trading filters for timing FX carry trades and found that they delivered improved risk adjusted performances over a long-only FX carry trade benchmark. Based on these findings, in Chapter 5 we develop and test several trading filters for market-timing FX carry portfolios. The market-timing signals are based on proxies for global volatility, liquidity and interest rate differentials. The aim of this research is to analyse the profitability of the carry trade during periods of global risk aversion or -appetite. Our findings suggest that market-timing the carry trade might be feasible using aggregated risk indicators for the generation of market-timing signals. Further, we detect a lookback bias in our analyses: Some market-timing signals which improve the carry trade performance by correctly timing the credit crisis, would not have been chosen before the credit crisis.

Carry trades are typically executed with leverage. We expand on research by Darvas [2009] who found that at high levels of leverage the risk-adjusted performance metrics to FX carry trading deteriorate significantly. We do so by testing a time-varying leverage algorithm based on the Kelly criterion. Moreover, we introduce a novel performance evaluation measure which allows for an evaluation of trading strategies with respect to capital growth and security. We find that conditional, time-varying, leverage models outperform optimal constant leverage levels for trading FX carry portfolios. Further, we demonstrate how the Sharpe ratio can lead to erroneous conclusions about the real-world profitability of leveraged trading strategies.

The remainder of this thesis is organised as follows. First, we provide an introduction into the foreign exchange market (Chapter 2). Second, we present current research on currency speculation and expand on the FX carry trading-style whose profitability is facilitated by the empirical failure of uncovered interest rate parity (Chapter 3). Third, we perform empirical research on asset allocation methodologies for setting up FX carry portfolios (Chapter 4). Fourth, we test market-timing indicators for trading FX carry portfolios (Chapter 5). Fifth, we analyse novel models for determining optimal leverage levels for FX carry portfolios (Chapter 6). Lastly, we summarise our main findings and draw a conclusion (Chapter 7).

Chapter 2

The Foreign Exchange Market

The foreign exchange market, or FX market, is the market where currencies are exchanged against each other. The FX market has some very unique characteristics which can be summarised as follows:

Market Size   The FX market is by far the most liquid market in the world. This high liquidity has pushed transactions costs to very low levels.

Market Structure   Exchange rates are traded around the clock in an interbank market. Customers do not have access to this market and have to refer to specialised dealers for quotes.

Market Participants   A very heterogeneous set of actors participates in the FX market. Market participants often do not share the same interests when trading currencies.

After defining how the term exchange rate is applied throughout the research, these characteristics will be outlined in the following sections.

2.1   What is an Exchange Rate?

An exchange rate represents the number of units of one currency that can be exchanged for a unit of another. There are two ways to express an exchange rate between two currencies (e.g., the US Dollar USD and the Euro EUR). One can either write $\frac{USD}{EUR}$ or $\frac{EUR}{USD}$. These are reciprocals of each other, if the exchange

rate S is the price for one EUR in USD ($S = \frac{USD}{EUR}$) and the exchange rate S' is the price for one USD in EUR ($S' = \frac{EUR}{USD}$), then $S = \frac{1}{S'}$ must hold.

Throughout this thesis an exchange rate S will denote the domestic currency price for one unit of foreign currency. If the EUR is regarded as domestic currency and the USD is regarded as foreign currency the exchange rate will be $S = \frac{EUR}{USD}$.

2.2 The G10 Currency Universe

Throughout this thesis, we focus on the G10 currency universe. The G10 currency universe consists of 9 out of the 10 most traded currencies, and the New Zealand Dollar, which is the eleventh currency when focusing on market turnover (see Borio et al. [2007]). The currencies of the $G10$ basket and their respective $ISO-4217$ currency codes are summarised in the Table below.

Country	Currency	Currency Code	Market Share in %
United States	Dollar	USD	88.70
Euro-area	Euro	EUR	37.20
Japan	Yen	JPY	20.30
Great Britain	Pound Sterling	GBP	16.90
Switzerland	Franc	CHF	6.10
Australia	Dollar	AUD	5.50
Canada	Dollar	CAD	4.20
Sweden	Krona	SEK	2.30
Norway	Krone	NOK	1.90
New Zealand	Dollar	NZD	1.40

Table 2.1: The G10 Currency Universe

Note that volume percentages in Table 2.1 would add up to 200% when considering all currencies: 100% for all the sellers and 100% for all the buyers.

2.3 Market Size

The foreign exchange market is the largest international financial market with an estimated daily turnover of USD 3.21 trillion (see Borio et al. [2007]). According to Borio et al. [2007] the foreign exchange transaction volume between foreign exchange dealers and both financial- and non-financial institutions more than doubled between April 2004 and April 2007. The increase of trading activity from these institutions is attributed to increased speculation by investors, who will have profited from the recent period of trending exchange rates and low market volatility (see Borio et al. [2007]), and to the growing importance of FX as an asset

class (see Section 3.1.1). Another cause for the surge in foreign exchange trading is the tendency of institutional investors to hold more internationally diversified portfolios, which involves buying and therefore usually hedging foreign currency in order to be able to enter into transactions abroad (see Borio et al. [2007]).

2.4   The Interbank Market

The FX market is a decentralised market with multiple dealers in many locations quoting and trading currencies simultaneously. The main trading centres are in London, New York, Tokyo, and Singapore, but banks throughout the world participate in the market. Currency trading happens around the globe for 24 hours a day and 5 days a week. As the Asian trading session ends, the European session begins, followed by the North American session and then back to the Asian session. Figure 2.2 depicts the largest providers of FX liquidity, as of May 2007. The Chicago Mercantile Exchange (CME) and the Philadelphia Stock Exchange (PHLX) are centralised exchanges that offer standardised derivative products on currencies.

Trading in the FX market can be divided into customer trading and interbank trading, which can be direct or brokered. Dealers provide liquidity by continually putting both bid (buy) and ask (sell) prices into the market. The bid/ask spread is the difference between the price at which a bank or market maker will sell (ask) and the price at which a market-maker will buy (bid) from a customer. The high amount of competition has caused bid/ask spreads to narrow drastically (see Lyons [2006]).

Electronic dealing platforms such as *EBS* or *Reuters Dealing* are currently established brokers. Borio et al. [2007] attributed the increase in global foreign exchange market turnover partly to the spread of such electronic trading platforms which enabled large financial institutions to set up automated trading systems, and provided better trading facilities to retail investors.

2.5   Traded Financial Instruments

The FX market offers a variety of financial instruments related to exchange rates. These are:

Spot   This trade represents a direct exchange between two currencies at the spot exchange rate S. A spot transaction is a two-day delivery transaction and involves cash rather than a contract.

Forwards   One way to deal with foreign exchange risk is to engage in a forward transaction. In this transaction, the parties agree on a spot transaction at a fixed exchange rate on some future date. Currency Forwards are over-the-counter (OTC) instruments and thus very flexible with regards to the duration and size of the contract.

Futures   Foreign currency futures are forward transactions with standard-ised contract sizes and maturity dates (maturities are usually at 3-month intervals). Currency futures are traded on centralised exchanges like the Chicago Mercantile Exchange, the Bolsa de Mercadorias e Futuros, the Budapest Stock Exchange, the Tokyo International Financial Futures Exchange, Euronext London and the New York Board of Trade (see Galati et al. [2007b]).

Swaps   In a foreign currency swap transaction, two parties exchange currencies and reverse the transaction after an agreed period of time. FX swaps are not standardised contracts and are traded on the OTC market.

Options   A foreign exchange option is a derivative where the owner has the right but not the obligation to exchange money denominated in one currency into another currency at an agreed exchange rate on a specified date. FX options are usually traded on the OTC market, although the Philadelphia Stock Exchange offers options with standardised strike prices and expiration dates to clients.

Figure 2.1 depicts the distribution of the traditional (over-the-counter) global foreign exchange market turnover over the available financial instruments.

2.6   Market Participants

The participating market actors in the FX market can have very different motivations for trading foreign exchange rates. In the following the main market participants, and their main interests will be described.

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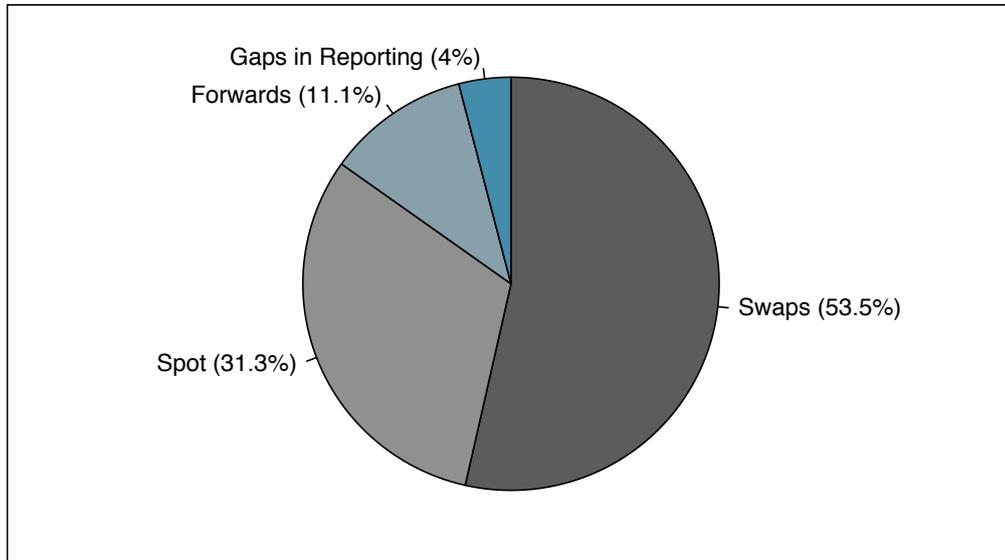
Figure 2.1: Over-the-counter FX Market Turnover Share of the main Financial Instruments (Source: Borio et al. [2007]).
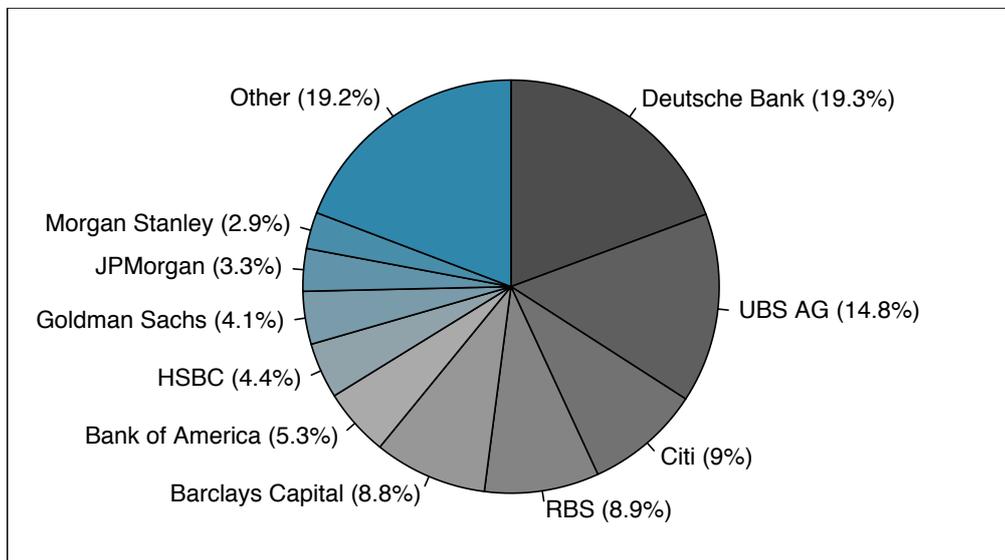
Figure 2.2: Market Share of the Largest Currency Dealing Institutions (Source: ECB [2007]).

Corporations   Corporations buy and sell foreign currency in order to pay for goods or services or to hedge future revenues in foreign currency. Multinational companies can have an unpredictable impact on exchange rates when very large amounts are traded due to reasons that are not widely known by other market participants (e.g., mergers or acquisitions).

Banks   The top-tier interbank market accounts for 53% of all transactions in the FX market (see Borio et al. [2007]). The investment banks act as liquidity providers for customers and also take part in speculative trading.

Central Banks   National central banks often have official or unofficial target rates for their currencies. They can use their often substantial foreign exchange reserves to stabilise the market. It is worth mentioning that considering the size of the FX market, direct intervention by central banks may not be effective. Central banks can however use their trades to signal their intentions to the market and attempt to arrest or reinforce a trend.

Mutual- and Pension Funds   Mutual- and pension funds use the foreign exchange market mainly to perform transactions in foreign securities. An investment manager with an international equity portfolio will need to buy and sell foreign currencies in the spot market in order to pay for purchases of foreign equities. Since the FX transactions are often secondary to the actual investment decision, they are not seen as speculative or aimed at profit-maximisation. Some investment management firms also have more speculative specialised currency overlay programmes, which aim to limit the risks of the currency exposure of the fund, and eventually generate additional excess returns. This attitude of fund managers towards the FX market has shifted in recent years, as non-traditional asset classes are looked to by investment professionals in a search for sources of returns which are uncorrelated to traditional asset classes (see Galati et al. [2007a]).

Hedge funds   Hedge funds have gained a reputation for aggressive currency speculation since 1992, when large foreign currency speculation by hedge funds forced the Pound Sterling to depreciate substantially in a short period of time. Galati and Melvin [2004] noted that Hedge funds participating in the FX market grew markedly over the period from 2001 to 2004 both in terms of number and

overall size.

Chapter 3

The Carry Trade

In this thesis we focus on the foreign exchange carry trade which denotes one of
the main known strategies for currency speculation. In Section 3.1 we will give
an overview on the practice of currency speculation. Investment strategies for
currencies and insights into the trading techniques adopted by FX hedge-funds
are discussed. In this section, the carry trade will emerge as a main driver behind
the profits of a whole industry. Section 3.2 will focus on the forward rate bias
(FRB), a major puzzle in financial economics which constitutes the theoretical
basis behind the profitability of carry trading. Finally, in Section 3.3 we will
discuss literature dealing directly with the phenomenon of the carry trade, its
profitability, trading strategies and drivers.

3.1 Currency Speculation

Professional investment managers constantly search for alternative sources of in-
come and diversification for their portfolios and the financial industry is keen to
provide the market with innovative products and investable indices also for the
realm of currency trading. Important developments and research results concern-
ing these topics will be discussed in the following sections.

3.1.1 Foreign Exchange as an Asset Class

Over the last 20 years professional currency speculators have been able to gener-
ate positive returns. Indices which track the performance of professional currency
managers exhibited good risk adjusted returns over this period. E.g., the Bar-
clays Currency Traders Index, a benchmark which measures the returns of global

currency managers, reveals healthy returns of 7.73% percent p.a. since 1987. [1]
A possible explanation for the ability of certain fund managers to generate positive returns by trading currencies might be the existence of profit opportunities generated by the activity of non-profit maximising actors in the FX market (e.g., central banks and corporations).

It has been shown that the returns to currency speculation exhibited very low, sometimes negative, correlations to more traditional asset classes like equities and bonds (see Pojarliev and Levich [2008] and DB [2009]). It is therefore not surprising that an increasing number of real money managers and hedge funds are treating FX as an asset class in its own, since it promises to act as a good vehicle for diversifying portfolios of traditional assets. An indication for this increased interest in FX as an asset class is given by the fact that the number of funds in the Barclays Currency Traders has grown from 44 in 1993 to 106 in 2006 (see Pojarliev and Levich [2008]). Galati and Melvin [2004] even attributed a part of the recent increased FX market turnover to the growing relevance of FX as an asset class.

Despite the increased popularity of currency trading, the sources of returns from professional currency speculation were not revealed to the public. Recent research into foreign exchange trading strategies and currency hedge funds helps to gain a better understanding of the mechanics of the industry of currency speculation and the drivers behind foreign exchange managers returns.

3.1.2 Popular FX Trading Strategies

Throughout the literature we find a set of recurring investment approaches when it comes to profitable currency speculation. The most widespread approaches are:

- Momentum strategies,

- Carry strategies,

- Valuation strategies,

- Volatility strategies.

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[1]Information retrieved from http://www.barclayhedge.com/research/indices/cta/sub/curr.html in April 2010.

There is evidence that these trading strategies or investment-styles could represent important tools in the investment processes of FX managers with a total return mandate (see Galati and Melvin [2004] and James [2005]). In the following paragraphs the rationale behind these investment strategies will be briefly discussed.

Carry The so-called *carry trade* denotes a very popular investment-style for currencies. In an FX carry trade, an investor borrows funds in a low interest rate currency and invests them in a higher interest rate currency. In doing so, the carry trader is betting that the exchange rate will not offset the positive interest rate differential that he is earning on the carry trade. Carry trading has produced good risk-adjusted returns in the past decades (see James [2005], Rosenberg [2003] or Vesilind [2006]).

Carry trading returns can be proxied by the *G10 Currency Harvest Index* by *Deutsche Bank*. The index tracks a portfolio which buys the 3 G10 currencies with the highest yields, while selling the 3 G10 currencies with the lowest yields. Investors can participate to the returns associated by such carry strategies, through a set of available products on the market, e.g., the *DBV* ETF[2].

Momentum or Trend Another popular strategy for currency speculation is *momentum trading*. Investors trading this investment strategy would buy currencies which exhibited a recent period of appreciation while selling currencies which exhibited a recent period of depreciation. Momentum trading in the FX market has produced positive returns in the past decades, as reported by James [2005], Lequeux and Acar [1998] or DB [2009].

As a proxy for FX momentum trading returns, the AFX Currency Management Index can be used. The AFX Currency Management Index is based on a set of trend-following moving average rules with different window lengths (32, 61 and 117 days). Lequeux and Acar [1998] showed that the AFX Index exhibited a high correlation with the returns of managed FX funds, indicating that professional currency managers might use trend following strategies.

Valuation A somewhat less popular, but academically very sound investment principle in the FX market is *valuation investing*. After determining a

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[2]An exchange traded fund by *Invesco Powershares* which tracks the DB Currency Harvest Index (see Invesco [2010]).

fair-value [3] for the currencies in the individual currency universe, the speculator would buy undervalued currencies and sell overvalued currencies. This trading rules can be motivated by empirical evidence which suggests that currencies often overshoot their fair values in the short run, and show a tendency to revert back toward their fair values in the longer run (see Pojarliev and Levich [2008]). Valuation trading strategies have generated positive returns in the past 20 years (see DB [2009]).

Investors can gain exposure to a valuation-based portfolio strategy through the *DB Currency Valuation Index* by *Deutsche Bank* (see DB [2007] and Figure 3.1)[4]

Volatility *Volatility trading* is perhaps the least implemented investment-style by professional currency managers, since it involves trading options, an activity practiced by about 10 percent of currency funds with a total return mandate (see James [2005]). A simple approach of profitably trading options in the FX market has been presented by James [2005]. The strategy, which sells short-dated straddles when the implied volatility is exceptionally high, was able to produce a Sharpe ratio of 0.607 in a backtest during the period betwen 1992 and 2005 (see James [2005]). James [2005] noted that - as the returns to volatility trading in the FX market are negatively correlated to carry- and momentum trading - the interest in such strategies is growing rapidly. Foreign exchange implied volatility can also be traded through specialised indices, e.g., the Deutsche Bank Currency Volatility Index (CVIX) which tracks 3-month implied volatility of a broad currency basket, weighted by market turnover (see DB [2007]).

A good overview of the returns to most of these FX investment-styles is provided by the *Deutsche Bank Currency Return Indices*, which are specifically designed to track the returns associated with these investment-styles (see DB [2007]). Figure 3.1 depicts the cumulative returns to momentum, carry and valuation investing, as well as a portfolio consisting out of the carry, momentum and valuation investment approaches (the *DB Currency Returns Index*). Figure 3.1

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[3]Purchasing Power Parity (PPP) in one of its many variants is a commonly used methodology to determine the long-run fair value of a currency.

The idea behind PPP is that a unit of currency should buy the same basket of goods in one country as the equivalent amount of foreign currency, at the actual exchange rate, can buy in that foreign country. If that relationship would not hold, then arbitrage possibilities could arise.

[4] The valuation index is constructed by *Deutsche Bank* and is based on the OECD Purchasing Power Parity figures (see EUROSTAT-OECD [2006] for the methodology behind the OECD PPP model.)

illustrates how the three single strategies have produced attractive returns during the last 2 decades, and how a portfolio of the different investment-styles produces a smoother cumulative return curve, due to positive diversification effects.
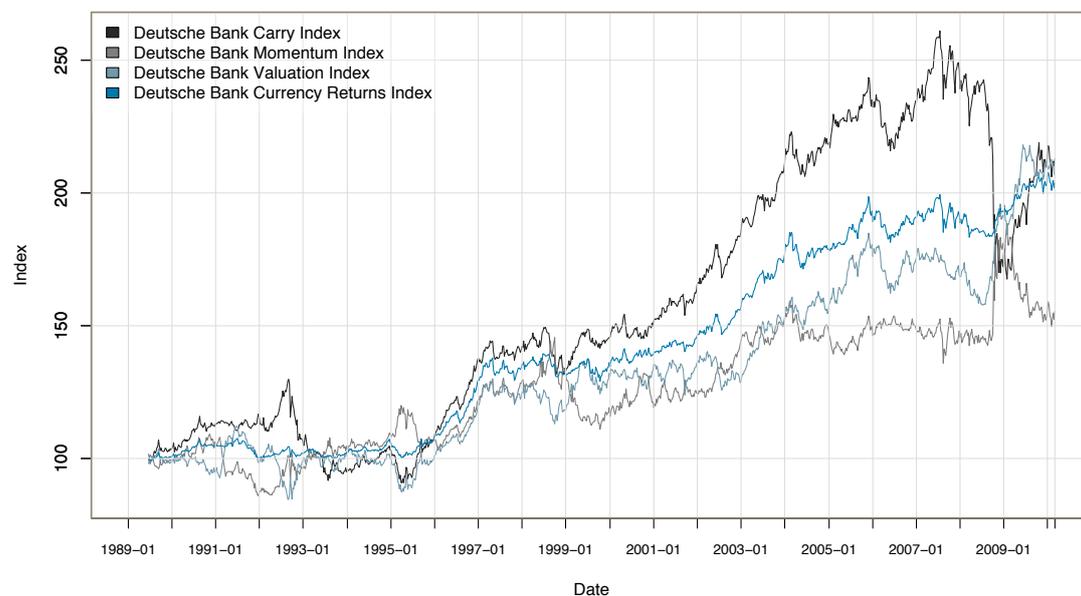
Figure 3.1: Historical Performance of Indices Tracking popular Foreign Exchange Trading Styles. Source: *Bloomberg, Deutsche Bank*

3.1.3 Benchmarks for Professional Currency Managers

At a first glance, currency speculation does not lend itself to traditional benchmarking. Unlike in the equity market, there is no natural market portfolio to track since each FX trade has the character of a long-short position. *De facto*, positive returns from currency speculation were traditionally termed as pure *alpha* returns (see James [2005]), since they were not correlated with traditional benchmarks such as equity market indices and lacked an own benchmark.

Recent literature on hedge funds performance evaluation opens up a different perspective on the evaluation of currency trading returns. In their seminal paper Fung and Hsieh [1997] showed that a vast part of hedge fund returns could be explained by easily replicable risk premia in the market. These replicable risk premia could not be attributed to individual manager skill and are termed *alternative beta's* by this line of hedge-fund research. Further research on the investment-styles adopted by hedge-funds has been performed amongst others by

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Hasanhodzic and Lo [2006], Jaeger [2005], Briand et al. [2009] or Anson [2008]. However, these studies have examined a general universe of hedge funds using mainly equity market and bond market factors as *alternative beta's*. In a recent paper by Pojarliev and Levich [2008] these analyses have been extended to the industry of currency hedge-funds.

Pojarliev and Levich [2008] examined the relationship between a data set of FX hedge-fund returns from the *Barclays Currency Traders Index* with proxies for the popular FX investment-styles momentum, carry, valuation and volatility. The aim of Pojarliev and Levich [2008] was to estimate what portion of currency trading profits by professional FX managers is due to exposure to these specific trading style or risk factors, and what portion is due to genuine manager skill (i.e. *alpha*).

The main findings of the study by Pojarliev and Levich [2008] were:

- A substantial part of the returns generated by FX hedge-funds can be explained by systematic exposure to known investment strategies.

- On average, professional FX managers do not exhibit significant ability to generate positive returns uncorrelated with the four investment-styles.

- Some FX funds show the ability to generate genuine *alpha*. This outperformance of traditional investment-styles seems to be the result of successful market-timing in some of the FX investment-styles.

The conclusion that Pojarliev and Levich [2008] drew from these results are that the definition and measurement of *alpha* returns in professional currency speculation should be changed. From their point of view, only those returns which are not associated to known and transparent currency trading strategies should be termed as *alpha* returns. Thus, following Pojarliev and Levich [2008], an aggregate of the main investment strategies for FX trading should constitute the new benchmark for professional currency managers. This notion is also advocated by *Deutsche Bank* in the prospectus for the *Deutsche Bank Currency Return Index* (see DB [2009]), which is marketed as the new benchmark for currency managers.

3.2 The Forward Rate Bias and the Carry Trade

The forward rate bias (FRB) is a major puzzle in financial economics. Since the hypothesis that the forward rate constitutes an unbiased estimator of future spot rates has been violated in empirical datasets, profit opportunities emerged for speculators willing to engage in risky foreign exchange trades. Such trades attempting to exploit the FRB puzzle are called *carry trades*. In the following sections we will discuss the theoretical construct leading to the formulation that the forward rate should be an unbiased predictor of exchange rates and present empirical findings in literature on the validity of this relationship. Subsequently, the concept of carry trading as a means to exploit the FRB is introduced.

3.2.1 Foreign Exchange Market Efficiency

The Efficient Market Hypothesis (EMH) states that financial markets are informationally efficient, i.e. prices fully reflect information available to market participants and therefore are unbiased in the sense that they reflect the beliefs of all investors about future developments of the assets (see Fama [1970]). Therefore, if the EMH holds, there should be no opportunities for market participants to earn excess profits from speculative activities.

The Rational Expectations Theory (RE) provides the basis for the EMH to hold. If investors have rational expectations, the outcomes that are being forecast ex-ante are assumed not to differ systematically from the ex-post realised outcomes, i.e. investors do not make systematic errors when predicting the future market prices.

Tests for the efficiency of the foreign exchange market have to take into account all the factors which influence the total return of an exchange rate position. When trading exchange rates, the total return of a speculative position which is opened at time t and closed at $t+k$ is dependent on three different factors. These factors are: the change in the spot exchange rate $\frac{S_{t+k}}{S_t}$, the earned interest rate in the home country $i_{t,k}$, and the earned interest rate in the foreign country with a similar maturity $i_{t,k}^*$. Equation 3.1 illustrates the calculation of the total return TR of a foreign exchange spot position:

$$TR_{t,t+k} = \frac{S_{t+k}}{S_t}(1 + i_{t,k}^*) - (1 + i_{t,k}) \tag{3.1}$$

In order to consider the FX market efficient, there should be no opportunity to

achieve systematic positive total returns from speculative activity in the foreign exchange market. A vast number of studies have investigated foreign exchange market efficiency by testing the validity of the following necessary conditions:

- The forward discount has to be equal to the interest differential (this no-arbitrage condition implies that covered interest rate parity (CIP) holds).

- The opportunity costs of holding a foreign exchange position, i.e. the interest rate differential, has to be offset by the shifts in exchange rates. The expected total return of an exchange rate position is thus zero (this uncovered interest rate parity (UIP) condition implies speculative efficiency of the FX market).

- The forward discount is a good predictor of the change in the future spot rate (implying CIP, UIP and RE).

Figure 3.2 presents the general relationship between interest rate differentials, the forward discount and expected exchange rate changes under efficient markets and rational expectations. Foreign exchange interest rate parity conditions determine how inflation differentials, interest rate differentials, forward exchange rates, and expected changes in exchange rates should be linked internationally in efficient markets. These international parity conditions would dictate that high inflation countries should see their currencies depreciate, whereas low inflation countries should see their currencies appreciate. They also indicate that the forward rate should act as an unbiased estimator of future spot exchange rates.
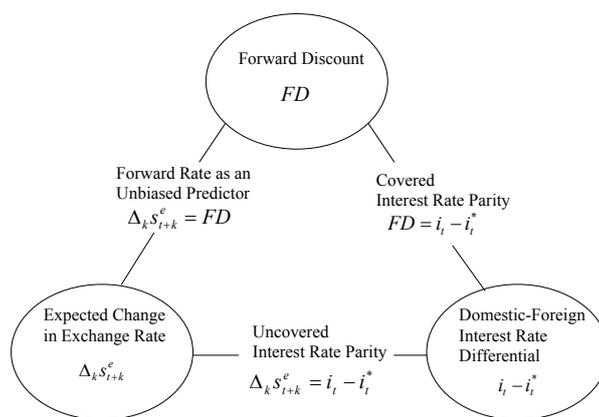
Figure 3.2: General Relationships in the FX Market under EMH and RE

In the following sections the CIP, UIP and the forward rate unbiasedness hypothesis (FRUH) will be briefly presented and the findings in academic literature about their empirical validity will be discussed.

3.2.2 Covered Interest Rate Parity

Theory In the absence of market frictions an investment in foreign currency that is fully hedged against foreign exchange rate risk should yield exactly the same return as a comparable domestic currency investment (see Rosenberg [2003]). The left hand side of Equation 3.2 illustrates the return an investor would earn when investing a unit of currency in the home country for k periods in a fixed-income security with interest rate i_t. The right hand side of Equation 3.2 represents the hedged return of investing the same amount abroad. This operation involves an exchange rate transaction, an investment in a foreign fixed income security with the interest $i_{t,k}^*$ and forward selling of the foreign currency at time k through a currency forward F_t^k. The no-arbitrage principle should ensure that both sides of the equation are equal. If this is not the case, arbitrageurs will exploit this risk free profit opportunity until the market prices are at equilibrium again.

$$1 + i_{t,k} = (1 + i_{t,k}^*)\frac{F_t^k}{S_t} \tag{3.2}$$

Hence, the forward rate of a currency forward has to equal the actual exchange rate adjusted by the interest rate payments on the spot position:

$$F_t^k = \frac{1 + i_{t,k}}{1 + i_{t,k}^*} S_t \tag{3.3}$$

Equation 3.3 can be reformulated and approximated by Equation 3.4, which constitutes the CIP condition:

$$FD = f_t^k - s_t = i_{t,k} - i_{t,k}^* \tag{3.4}$$

Where FD is the forward discount rate, f_t^k is the logarithm of the forward exchange rate at time t for k periods ahead and s_t is the logarithm of the spot exchange rate at time t. If the relation in Equation 3.4 holds, there will be no advantage to investing in an exchange rate of a specific country while hedging the foreign exchange risk on the forward market. Equation 3.4 can be reformulated to an econometric regression equation, generally applied to test for the empirical

validity of CIP (see Sarno and Taylor [2002]):

$$FD = \alpha + \beta(i_{t,k} - i_{t,k}^*) + \epsilon_t \tag{3.5}$$

For CIP to hold empirically, the regression estimation should produce an α parameter differing insignificantly from zero, a β parameter differing insignificantly from unity and non serially correlated regression errors ϵ_t.

Empirical Evidence Studies on the validity of CIP have often been based on regression analysis, generally performing regressions based on Equation 3.5. Frenkel and Levich [1975] performed early tests on CIP. Using weekly observations from January 1962 to November 1967, they found that covered interest parity held for three-month horizons after accounting for transactions costs. Later Frenkel and Levich [1977] extended their study into three periods (1962-67, 1968-69, and 1973-1975) in order to differentiate between different foreign exchange rate regimes. This confirmed their previous findings: CIP still holds during these periods even when the effect of transaction costs is taken into account. Subsequent studies supporting the absence of arbitrage opportunities in the foreign exchange market include Rhee and Chang [1992], Fletcher and Taylor [1994] and Juhl et al. [2006].

The main conclusion that can be drawn by this line of research is that CIP holds. Some tests exhibit *alpha* values which are significantly different from zero, but market features as taxes, illiquidity, political risk and transaction costs are then held responsible for these results (see Taylor [1987]).

Taylor [1987] questioned previous studies reporting evidence of deviations from CIP, since they were not based on contemporaneous high frequency data from currency and interest rate markets, and thus produced results that could not be implemented realistically in a trading situation. Taylor tested for the validity of CIP using a high-frequency data set composed of interest rate and exchange rate data points at about one minute intervals during the most active trading hours in London over three days in 1985. Taylor found strong support for CIP, since he did not find any profitable arbitrage opportunity within the data set, thus confirming the results from previous studies.

3.2.3 Uncovered Interest Rate Parity and the Forward Rate Bias

Theory   In a fully efficient market, actual prices should incorporate all information which is available to market participants (see Sarno and Taylor [2002]). According to the efficient markets hypothesis, it should not be possible for an investor to earn excess returns from speculation, since all potentially relevant future information would have been already discounted into the market price (see Fama [1984]). Therefore the expected total return from holding a certain currency rather than another, should be zero. Since the total return of an exchange rate position is made up of a risky exchange rate component as well as a risk-free interest rate component, the former is expected to be offset by the latter. By extension therefore, the expectations of spot rate changes should be explained by Equation 3.6:

$$\Delta_k s_{t+k}^e = i_{t,k} - i_{t,k}^* \tag{3.6}$$

Where s_t is the logarithm of the spot exchange rate S at time t, $i_{t,k}$ and $i_{t,k}^*$ are the nominal interest rates on similar domestic and foreign securities respectively (with k periods to maturity), $\Delta_k s_{t+k}^e$ denotes the market expectation of the change in the exchange rate from t to $t+k$ based on information at time t.

A second necessary condition, besides the validity of the efficient market hypothesis for deriving the UIP relationship is the rational expectations hypothesis, which states that market participants behave rationally and thus the deviation between their market forecasts and realised spot exchange rate changes should be unpredictable and zero on average. If investors have rational expectations, Equation 3.7 must hold.

$$s_{t+k}^e = s_{t+k} + u_{t+k} \tag{3.7}$$

The term u_{t+k} represents an error term, with a mean equal to zero, s_{t+k}^e and s_{t+k} are respectively the logarithms of the expected exchange rate in t for k periods ahead and the logarithm of the realised exchange rate k periods ahead.

By substituting Equation 3.7 into Equation 3.6 we obtain Equation 3.8, which describes the uncovered interest rate parity UIP condition when investors are rational and markets efficient:

$$\Delta_k s_{t+k} = i_{t,k} - i_{t,k}^* + v_{t+k} \tag{3.8}$$

Where v_{t+k} is an error term with mean zero and no serial correlation. Equation 3.8 states that the returns from the spot exchange rates should be directly

offset, on average, by the relevant interest rate differential of that currency position. Reformulating Equation 3.8 by using the relationship for the covered interest rate parity (see Equation 3.4), the uncovered interest rate parity can be interpreted as the hypothesis that the forward rate is an unbiased predictor of the future spot rate, i.e. that the forward discount accurately predicts the changes in spot exchange rates:

$$\Delta_k s_{t+k} = f_t^k - s_t + u_{t+k} \tag{3.9}$$

According to UIP, the interest rate differential should be offset by the appreciation of the low yielding currency and the depreciation of the high yielding currency. The condition expressed by Equation 3.8 can be tested through the Fama-regression Equation 3.10:

$$\Delta_k s_{t+k} = \alpha + \beta(i_{t,k} - i_{t,k}^*) + \epsilon_{t+k} \tag{3.10}$$

Where $\Delta_k s_{t+k}$ is the change in the spot rate from time t to k, $i_{t,k}$ is the interest rate for the home currency at time t, $i_{t,k}^*$ represents the interest rate for the foreign currency at time t and ϵ_{t+k} are the regression residuals with a mean equal to zero.

By substituting Equation 3.4 into the econometric regression Equation 3.10 for testing the uncovered interest rate parity, the typical regression for testing for the unbiasedness of the forward rate as a predictor for the future spot exchange rate can be obtained (Equation 3.11). The forward rate unbiasedness hypothesis (FRUH) states that the forward rate should correctly predict future spot exchange rates.

$$\Delta_k s_{t+k} = \alpha + \beta(f_t^k - s_t) + \xi_{t+k} \tag{3.11}$$

Where ξ_{t+k} is a disturbance term. If agents are risk-neutral and have rational expectations, as in the UIP regression, we should expect the slope parameter β to be equal to unity and the disturbance term ξ_{t+k} - the rational expectations forecast error - to be uncorrelated with information available at t. This property of the disturbance term follows from a standard property of rational expectations forecast errors that $E[\xi_{t+k}|\Omega_t] = 0$, where $E[.|\Omega_t]$ denotes the mathematical expectation conditioned on the information set available at time t, Ω_t.

Since CIP has been shown to hold in practice, tests for UIP and FRUH should produce very similar results. The literature review is therefore congruent for both

hypotheses.

Empirical Evidence Interestingly, the vast majority of literature states that the UIP does not hold empirically. Meese and Rogoff [1983a] and Meese and Rogoff [1983b] found that a random walk model consistently forecasts future spot rates better than the any alternative structural models, including the forward rate model at horizons under two years. Empirical studies based on the estimation of Equation 3.10 and Equation 3.11, generally report results that contradict the UIP and FRUH hypotheses, thus disproving the efficient markets hypothesis under risk neutrality. The estimated β coefficients can be shown to be statistically different from unity in the majority of cases. Often the estimated β coefficient even assumes negative values, implying that the forward premium systematically predicts changes in the spot exchange rate in the wrong direction. Froot and Thaler [1990] reported that the average *beta* coefficient across 75 published estimates is -0.88. This empirical finding of the misprediction of the direction of exchange rates by the forward premium has been called the forward rate bias FRB.

Conversely, studies which examined very long data sets claim that UIP holds in the very long run, but can deviate for extended periods of time due to slow adjustment of expectations to actual regime changes or to peso-effects (see Lothian and Simaan [1998] and Lothian and Wu [2003]).

The level of economic development of countries and the length of the yield maturities seem to have an influence on the strength of the departures from UIP. Bansal and Dahlquist [2000] and Frankel and Poonawala [2006] compared the forward rate bias in major currencies with emerging market currencies and have found that the bias is weaker in the emerging market currencies, since the *beta* coefficient there is, on average, slightly above zero. Also, UIP is more likely to be violated for short maturity bonds, than on longer horizons. Alexius [2001] and Chinn and Meredith [2005] have shown that the negative β coefficient does not arise when using long maturity bonds, even in the major currencies.

3.2.4 Explanations for Empirical Failure of UIP

Meredith and Ma [2002] note that the *FRB* puzzle must be caused by the failure of one or both parts of the joint hypothesis of efficient markets and risk neutrality. Efficient markets make sure that the expectations of future variables, including

the foreign exchange rate, embody all information available at the time when the expecations are formed. Risk neutrality implies that the forward rate equals the market expectation of the future spot rate. Combining these postulates in the risk-neutral efficient-markets hypothesis implies that the deviation between the forward rate and the realisation of the future spot rate is a white-noise error term not correlated with past information. The Fama-regressions (see Equation 3.10) should then yield a beta coefficient of unity.

Thus, since *UIP* has been shown to fail empirically, possible explanations include irrationality in investors expectations formation or risk-averse speculators. Moreover, we have identified two additional categories which provide of potential explanations for the *FRB* puzzle, namely *in-sample bias* and *regime shifts and heterogeneous beliefs*. In the following paragraphs we will provide an overview of the literature analysing explanations behind the failure of *UIP*.

Irrationality

Explanations based on irrationality assume that the failure of UIP stems from irrational traders whose predictions about future prices are systematically biased. This scenario conflicts with the rational expectations hypothesis.

A variety of studies have examined the relationship between the errors of price forecasts in surveys and predictable elements of excess returns (see e.g. Froot and Frankel [1989], Chinn and Frankel [1994], Cavaglia et al. [1993], Bacchetta and Wincoop [2005]). These studies consistently found that the measures of forecast errors had a strong relationship with the excess returns. Thus, Froot and Frankel [1989] concluded that the forward rate bias is due to errors in forecasts by market participants and does not arise as a compensation for risk.

A possible explanation for the emergence of such forecast errors has been provided by Lewis [1989] who demonstrates that they can be caused by changes in the markets that are not fully understood by market participants. The reasoning behind this is that market participants will gradually update their beliefs that a new regime is in place, generating systematic forecast errors during the transition. A similar explanation is given by Froot and Thaler [1990] who noticed that the FRB might be caused by investors which are either slow in adapting to interest rate changes, or are unable to do so because of regulatory restrictions. The slow-mover hypothesis of Froot and Thaler [1990] provides an explanation why high interest yielding currencies continue to appreciate, whereas low yielding currencies continue to devalue over prolonged periods.

In-Sample Bias

Engel [1996] argued that tests for uncovered interest rate parity could suffer from an in-sample bias. Such an in-sample bias arises when the information set of the researcher differs from that of the market. When that happens, regressions could erroneously reject or accept the efficiency hypothesis (see e.g. Krasker [1980]). Incongruency in information sets can be caused by peso effects or learning effects.

Peso effects are characterised when low probability events such as a currency crisis occur in the data and models are unable to describe such extreme events appropriately [5].

By contrast, learning effects denote a situation where the market participants are not sure if a change in regime has taken place or not, or they do not fully understand all the relevant information for the exchange rates contained in a policy change.

By analising FX options data, Bates [1996] showed that expected exchange rate distributions vary considerably over time, especially with regards to skewness and kurtosis. Although peso effects emerge, he rejects that they were the cause for the empirical deviation from UIP between the USD and DEM (German Mark) during the 1980s.

Lewis [1989] indicates that the general underprediction of the US Dollar strength in the first half of the 1980s can be attributed to learning effects. She provides evidence that the money demand in the United States experienced a sensible increase during those years. She argues that the increase in demand was not offset by an appropriate increase in the supply of money. This led to a steady appreciation of the USD. Since markets did not adapt immedeately to the accelerating demand for money, exchange rate expectations and forward rates persistently underestimated the appreciation of the USD.

The problem with accepting peso problems, bubbles or learning as explanations for the forward bias is that the large number of econometric studies encompassing a large range of exchange rates and sample periods, have found that the direction of the bias is the same under each scenario (see e.g. Lewis [1989]). This is not in line with the learning explanation since agents cannot forever be learning about a unique regime shift. Similarly, the peso problem and speculative bubbles are essentially a small-sample phenomenon which cannot explain the fact that estimates of the beta parameter in the Fama-regressions are generally negative.

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[5]see e.g. the *Peso crisis 1994*, when there was a sudden devaluation of the Mexican Peso that caused other currencies in the region to decline

Regime Shifts and Heterogeneous Beliefs

The in-sample bias literature is closely related to literature which attributes the *FRB* to regime shifts and heterogeneous beliefs. These theories account for systematic deviation from UIP and for long-lasting trends of exchange rate appreciation and depreciation.

Engel and Hamilton [1990] study the phases of USD strength (early 1980's) and weakness (1985 to 1988) and find that forward rates systematically underpredicted these trends in the USD. They argue that exchange rates incur long trending periods which lead currencies to have long periods of appreciation and depreciation. Engel and Hamilton [1990] proposed a model where exchange rates follow two normal distributions. More specifically, they set up a segmented trends model with an appreciating and a depreciating regime. In the model, the parameters of both distributions and whether they are in regime one or regime two are known to investors. On the other hand, they do not know at which point in time the regimes switch. Since the investors are assumed to be risk-neutral, the forward rate is given by a probability-weighted average of their regime predictions. Such predictions lead to a misalignment between forward and future spot exchange rates. The resulting bias is an increasing function of the probability of a regime shift and of the expected magnitude of the exchange rate movement in case of a regime shift. Whereas this specification of Engel and Hamilton [1990] failed empirically, an extension of the model by Kaminsky [1993] generated more favorable results. Kaminsky [1993] assumes that investors try to predict a regime shift by evaluating information from announcements of the Federal Reserve Board (FED). Another succesful model has been proposed by Evans and Lewis [1995] postulating exchange rate jumps when regimes switch. The models by Engel and Hamilton [1990], Kaminsky [1993] and Evans and Lewis [1995] are primarily descriptive since they do not aspire to explain the reasons for changes in FX regimes.

Despite extensive research, there does not exist a structural model delivering reliable predictions for short-term exchange rate fluctuations (see e.g. Rosenberg [2003]). Thus, it is no surprise that expectations are very varied amongst survey respondents. That is what has been found by Tagaki [1990] by analysing different surveys on exchange rate predictions. Rogoff [1996] and Rogoff [2002] found that long-term exchange rates are influenced by inflation differentials. Taylor and Allen [1992] evaluated results from a quastionnaire survey and found that

long-term predictions are formed based on fundamentals, while in the short run investors base their decisions strongly on technical analysis. This is confirmed by Frankel and Froot [1990]. Using data from various surveys, Frankel and Froot [1990] study how exchange rate expectations are formed by investors. They distinguish between technical speculators, who extrapolate their forecasts from current exchange rate trends, and fundamental investors, who assume that exchange rates converge to some long-term equilibrium. Based on these findings, Ahrens and Reitz [2005] propose a model where investors are considering both the views of technical traders and fundamental investors. In the technical regime exchange rate changes are predicted on the basis of a simple momentum strategy. In the fundamental regime exchange rate changes are formed based on deviations from purchasing power parity. Investors form their expectations by a weighted average of the fundamental and the technical views. Ahrens and Reitz [2005] demonstrate how exogeneous shocks can cause departures from the fair value which explain not only UIP, but also long term exchange rate trends.

Risk Premia

The theories presented in the above points assume risk neutrality. This means that investors exploit all available opportunities for profit in the markets irrespecitively of the risks involved. Since real-world investors do exhibit aversion to risk, these theories are based on unrealistic assumptions (see Kohler [2008]). A risk-averse investor will carefully balance his profit opportunities against the risks of the specific investment. Thus, the risk premia literature examines whether deviations from *UIP* arise as a compensation for currency risk exposure.

Studies relating the *FRB* puzzle to risk utilise different methodologies which range from CAPM and conditional CAPM settings to portfolio-balance and general equilibrium models (see e.g. Kohler [2008])

Bansal and Dahlquist [2000] tested for currency risk premia in a CAPM framework. They calculated deviation from UIP for 27 currencies against the USD. As a benchmark portfolio they chose the aggregate performance of U.S. equities. In their regressions, the equity risk factor failed to explain the cross sectional variation in currency risk premia. Bansal and Dahlquist [2000]'s estimation is based on a constant beta specification and cannot capture time-variation in risk premia. Mark [1988] additionally incorporated time variation in the beta coefficient of the CAPM model. He used a weighted average of the US, German, Swiss, Japanese and British stock market as the market portfolio. Mark [1988] found

that his model could not be rejected by the data, and interpreted his findings as providing evidence for currency risk premia being driven by international equity markets. Unfortunately, he does not provide any goodness-of-fit statistics so that the explanatory power of the model can not be accurately assessed. Lustig and Verdelhan [2005] obtained good results when estimating a *CAPM* model by using interest rate differentials as explanatory variables. Lustig and Verdelhan [2005] find R-squared measures of up to 36%, i.e. their model could capture about a third of the total variation in currency risk premia.

If the negative *beta* coefficients in the Fama-regression were due to the omission of a time-varying risk premium, the vast majority of studies, which are estimated using ordinary least squares, would yield biased and inconsistent estimates of β due to the presence of an omitted risk premium in the Fama-regression (see Fama [1984] and Liu and Maddala [1992]). Fama [1984] and Hodrick and Srivastava [1986] found that the forward rate bias bias can be explained by a nonzero risk premium. Conversely, Froot and Frankel [1989] later inferred from their studies that the systematic portion of forward discount prediction errors does not capture a time-varying risk premium. The results of Frankel and Poonawala [2006], which showed that the forward rate bias is larger in currencies of developed countries than in emerging market currencies also contrasts with the suggestion that the phenomenon of the forward rate bias can be attributed to a risk premium. If that were truly the case, the FRB would be greater for emerging market currencies, since they bear more risks, than in developed market currencies.

3.2.5 Exploiting the Forward Rate Bias through Carry Trading

The phenomenon of the forward rate bias creates the possibility of implementing trades in the foreign exchange market that generate profits by exploiting this market inefficiency. These trades involve buying high yielding currencies and at the same time selling low yielding currencies. Since high yielding currencies have tended to depreciate less - and low yielding currencies have tended to appreciate less than suggested by financial theory, this style of trading is expected to produce positive excess returns. Betting on the FRB in the foreign exchange market is also called *carry trading* (see Rosenberg [2003]), since if the spot exchange rate does not change over time the investor earns interest by *carrying* the FX position.

Carry strategies can be implemented as a dynamic borrowing and lending

strategy in two currencies or through a simple long or short speculation in the forward market. The implementation of carry trades with currency forwards is the most frequently applied of the two alternatives. At time t the investor will buy a currency forward which sells at a discount, i.e. he will agree to buy the high yielding currency against the low yielding currency on a specified date in the future. When the forward contract reaches maturity the trader will be able to buy the currency at a lower price than the actual market price and make an immediate profit, as long as the exchange rate have did not offset the earned interest. When implementing a carry trade through a forward contract, the return of the carry trade $r_{t,t+k}^{carry}$ can be computed as:

$$
r_{t,t+k}^{carry} = \begin{cases} f_t^k - s_{t+k}, & \text{if } i_{t,k} < i_{t,k}^* \\ s_{t+k} - f_t^k, & \text{if } i_{t,k} > i_{t,k}^* \\ 0, & \text{if } i_{t,k} = i_{t,k}^* \end{cases} \tag{3.12}
$$

An atypical approach to implementing carry trades involves currency options trading. Since options are priced through a replication argument including the eventually biased forward rate, they are also mispriced in the case where the forward rate bias continues to exist. For an example of such an implementation we refer to Hochradl and Wagner [2010].

3.3   The Carry Trade in Literature

In Section 3.2 we reviewed the literature on the forward rate bias puzzle, which focuses implicitly on the mean return of the carry trade. Motivated by the important profits and practical implications of the carry trades, a good number of research publications have focused directly on the carry trade in recent academic literature.

Research on the carry trade can be divided into research concerning the formulation and refinement of profitable carry trading strategies, and into empirical research which examines the drivers behind the returns to carry trading. Furthermore, since activity of speculators in the interbank FX market is relatively opaque, we will look at empirical evidence for carry trading activity by large institutional investors. In the following section these branches of research on the FX carry trade will be discussed.

3.3.1 The Profitability of the Carry Trade

Simulations of carry strategies have been performed in literature amongst others by Rosenberg [2003], Hochradl and Wagner [2010] and Vesilind [2006]. Although the algorithms and currency baskets used for the strategy simulations differ slightly, the carry strategies were always able to produce substantial excess returns. Many investment banks also simulate the performance of carry strategies applying similar methodologies and getting similar results as the models analysed in academic literature (see Gyntelberg and Remolona [2007]).

The reported profitability of carry trading strategies is in line with the conclusions of academic research, which reports the existence of a forward rate bias in foreign exchange forward rates (see Section 3.2.3). Since historically high (low) yielding currencies have tended to depreciate (appreciate) less than suggested by financial theory, it is obvious that carry trade strategies which assume long (short) positions in high (low) yielding currencies, have generated profits.

The reasons for the existence of these carry trade profits over the examined data sets are not clear. Possible reasons for the profitability of carry trading are the same as those evaluated by researchers in attempting to explain the empirical failure of uncovered interest rate parity, e.g., risk-premia, forecast errors and rational bubbles. As in the case of the failure of UIP, there is no generally accepted theory which explains the profitability of the carry trade.

A possible explanation for the enduring profitability of the carry trade has been given by Lyons [2006], with the limits to speculation hypothesis (LSH). The LSH states that large financial institutions will not allocate risk capital to trading strategies with Sharpe ratios under a certain threshold. Lyons [2006], reported that major financial institutions show little interest in allocating capital to trading strategies with Sharpe ratios below 0.4. Following this assumption, if returns from carry trading yield insufficient risk-adjusted profits they will not be exploited by large speculators, thus leaving the opportunity for investors willing to take the risks associated with this strategy to generate returns from carry trading.

Hochradl and Wagner [2010] specifically addressed the question whether the LSH has relevance in the case of the carry trade. By simulating carry trading strategies and showing that the performance measures of the carry strategies easily exceed the Sharpe ratio threshold of 0.4, they strongly questioned the validity of the LSH as an explanation for enduring carry trade profits.

Similarly, Burnside et al. [2006] questioned the practical relevance of the carry trade, noting that carry trading strategies typically generated low absolute returns which would make it necessary to wager large amounts of money to achieve acceptable levels of return. Trading such large amounts would create market frictions like price pressure, i.e. worse execution prices than actual market prices (i.e. slippage) and wider bid-ask spreads. Burnside et al. [2006] noted that the existence of such market frictions may erode the profits inherent to the carry trade.

3.3.2 Evidence for Carry Trading Activity

The carry trade is an investment strategy which is widely used by practitioners (see Burnside et al. [2006]). Galati and Melvin [2004] even attributed the surge in trading activity in the foreign exchange markets, which emerged in the *2004 BIS Triennial Survey* (see Galati et al. [2007a]), to a large extent to the growing volume of FX carry trade positions held by market participants, especially large financial institutions such as hedge funds and *CTA's*. The magnitude of the international exposure to the carry trade is very difficult to quantify through publicly available information however, since individual transaction data is not available. Moreover, the distinction of carry trade positions from trades initiated for other reasons is problematic, also because of a lack of consensus about how a carry trade should be defined (see McGuire and Upper [2007]).

Due to these reasons, one has to rely on a set of potential indicators to detect carry trade activities in the foreign exchange markets. These indicators include balance sheets of investment banks, positioning data from the OTC market and futures exchanges, correlation of transaction volume data with measures of carry attractiveness and statistical analysis of hedge fund returns.

Analysis of the balance sheets of investment banks could provide some evidence for the existence of carry trades. Banks serve as market intermediaries providing loans and taking deposits in the currencies used by carry trade investors, as well as holding carry positions for proprietary speculative reasons. This would generate higher liabilities denominated in the carry trade funding currencies and higher assets denominated in the target currencies on the banks balance sheet (see Galati et al. [2007b]). Since carry trades often involve derivative instruments, especially forwards, which do not appear on the banks balance-sheet, this type of data can only be useful in detecting carry trade activity executed in the

cash market. Also, it is not clear from the balance sheets whether the positions are actually caused by carry trade activity or by lending and borrowing related to different activities. These reasons make the establishment of direct links between balance-sheet data and the existence of carry trades in the market very difficult.

Galati et al. [2007b] reported evidence of a rising role of the Japanese Yen JPY and the Swiss Franc CHF as funding currencies, since claims in these currencies on balance sheets of banks have been rising in absolute terms in the recent years. Since both these currencies have exhibited very low yields throughout the last years, this might be an indication for rising carry trade activity.

Data from the Chicago Mercantile Exchange on open currency futures positions has been analysed by McGuire and Upper [2007]. They noted that the rise in speculative short positions in Japanese Yen JPY futures grew as the JPY depreciated from mid-2006 to February 2007. A quantitative study of such correlations between measures of carry trade attractiveness like interest rate differentials and carry-to-risk ratios has been conducted by Galati and Melvin [2004] and Galati et al. [2007b]. Correlation analysis between carry-to-risk ratios[6] and foreign exchange market turnover is reported to be varying but high enough to suggest a relationship between the market turnover and carry trade activity. The highest correlations existed for the Norwegian Krone NOK (0.79), the Australian Dollar AUD (0.53), the South African Rand ZAR (0.36), the Mexican Peso MXN (0.28) and the New Zealand Dollar NZD (0.24). Galati and Melvin [2004] tested the impact of interest rate differentials and trends in exchange rates on the change in OTC market turnover of the exchange rate using *BIS* survey data from 1992 to 2004 . They conclude that turnover growth is positively related to increases in interest rate differentials and past exchange rate price changes. These results would seem to indicate that increased market activity in an exchange rate is triggered both by carry trading and by trend following behaviour of speculators.

A further indication for the practical relevance of the carry trade comes from the analysis of hedge fund returns. McGuire and Upper [2007] performed style analysis regressions on hedge fund returns and proxies for returns related to carry trading. They conclude that carry trading returns are statistically significant determinants of hedge fund performance. This result has been confirmed also by Jylha and Suominen [2009] and Pojarliev and Levich [2008] (see Section 3.1.3).

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[6]Galati et al. [2007b] computed carry-to-risk ratios as a measure of the attractiveness of a currency for carry trading. The carry-to-risk ratios were calculated through dividing the interest rate differential by the historical volatility of the currency.

The fact that investment banks are offering research and tradeable indices which target specifically the carry trade in foreign exchange, provides an additional qualitative confirmation for the practical relevance of carry trading found in the statistical regressions.

Although it seems difficult to detect evidence for carry trading from publicly available data, the aggregation of the above mentioned indications makes it possible to draw the conclusion that carry trading constitutes an important reality in foreign exchange trading.

3.3.3 Risks Associated with Carry Trading

Despite having produced good risk adjusted returns in the last two decades, there are considerable risks associated to carry trading strategies. The most relevant being the large potential drawdowns associated with periods of collective unwinding of carry positions, and the meltdown of diversification benefits during phases of financial market turmoil.

Collective Unwinding of Carry Positions   A major property of FX carry trade returns is their exposure to currency and stock market crashes. Galati et al. [2007b] suggested that the reason behind the profitability of carry strategies comes from the positive feedback caused by the build-up of large carry positions. Active carry trading from the investment community would have the effect of further strengthening high yielding currencies and weakening low yielding currencies, and thus lead to an ever increasing profitability of the carry trade.

If liquidated collectively, these large carry trade positions in the portfolios of institutional investors can trigger huge volatility increases in exchange rates, causing high yielding currencies to depreciate, and low yielding currencies to appreciate substantially in short periods of time (see Gagnon and Chaboud [2007]). According to Galati et al. [2007b], the sudden and sharp appreciation of the Japanese Yen JPY during October 1998 provides a good example for the drastic effects a global unwinding of carry trade positions can have on the involved currencies.

This intuition is confirmed by Brunnermeier et al. [2008] who showed that carry trade returns are negatively skewed and that therefore carry trading exposes the speculator to so called *crash risk*. This negative skew is attributed to the sudden unwinding of large carry trade positions by large investors described by

Galati et al. [2007b]. Further, Brunnermeier et al. [2008] documented that such carry trade unwinding tends to occur in periods of stock market or currency crises, in which risk appetite and funding liquidity typically decrease.

Meltdown of Diversification Benefits   A further important property of carry trade returns is the low correlation to more traditional asset classes like equities and bonds. This property has been reported by e.g. Jylha and Suominen [2009] or DB [2009]. Recent research by Kohler [2007] analysed correlation dynamics between returns on a global equity index and returns of carry trades. Kohler [2007] showed that the correlation between stocks and carry strategies significantly increases during periods of financial turmoil. Carry traders which set up carry trades to enhance their portfolio diversification will therefore experience a severe diversification meltdown in times of global stock market crises.

3.3.4   Carry Trade Dynamics and Risk Premia

An important line of research concerning the dynamics behind the carry trade is the analysis of factors which could explain the risk-premium associated to carry trading profits.

Several authors have expressed the idea that constructing indices which track the general risk-appetite in the markets could be useful for timing FX carry trades (see Rosenberg [2003] and Vesilind [2006]). Risk factors used by the industry to measure global risk-appetite include the US Treasury Yield Error[7], the 10-year Swap Spread, the Emerging Markets Bond Index spread, the US High Yield [8] spread and FX market volatility (see Vesilind [2006]).

Academic research in this field has been conducted by Burnside et al. [2006] by performing regressions of the returns to carry strategies on a variety of risk factors. The risk factors include U.S. per capita consumption growth, the returns to the S&P500, the Fama-French stock market factors[9], the slope of the yield curve computed as the yield on 10-year U.S. treasury bills minus the 3-month U.S. treasury-bill rate, the luxury retail sales series constructed by T-Sahalia et al. [2004], U.S. industrial production, the return to the FTSE 100, and per-

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[7]i.e. the difference between on-the-run and off-the-run government bond interest rates

[8]i.e. yield on non-investment grade debt

[9]Fama-French factors are Rm-Rf, *SMB* and *HML*, respectively (see Fama and French [1992] for details)

capita UK consumption growth. However other than two notable exceptions, i.e. the Fama-French *HML* factor and real UK consumption growth, no risk factor is found to be significantly correlated with the returns from a set of different carry strategies. Burnside et.al. therefore conclude that risk factors do not offer an empirically plausible explanation for the returns to carry trading in foreign exchange.

Burnside et al. [2006] also examined the relationship between monetary variables and the returns to the carry trade. The carry trade returns are regressed on the Federal Funds rate, the rate of inflation, and the growth rates of four different measures of money supply. Burnside et al. [2006] found significant relationships between carry strategy returns and inflation and the Fed funds rate. They consider their results as supportive of theories that suggest a link between monetary policy and the empirical failure of UIP.

More recent research found interesting relationships between risk-factors and carry trade returns. Wagner [2009] showed that the carry trade strategy entails a time-varying risk premium. Menkhoff et al. [2009] found a significant negative return return co-movement of high interest rate currencies with global volatility, whereas low interest rate currencies provided a hedge against volatility shocks. Christiansen et al. [2009] followed a similar line of research. By estimating factor models for carry trade strategies where regression coefficients are dependent on market volatility and liquidity, they show that the carry trade exhibits a higher exposure to the stock market in volatile periods. These results are in line with the findings of Kohler [2007]. By looking at the behaviour of carry trade strategies during the credit crisis from 2007 to 2010, Vistesen [2009] reached very similar conclusions. By estimating a factor model which relates FX carry trade returns to equity returns and market volatility Vistesen [2009] showed that low yielding currencies such as the JPY and the CHF can be modelled as a negative function of equity returns and positive function of market volatility.

Dunis and Miao [2007] examined the behaviour of carry trade returns during different regimes of FX market volatility, proxied by the *RiskMetrics* volatility of a portfolio of currencies weighted by their market turnover. They find that the returns to carry trading are higher during periods of low FX market volatility than during periods of high FX market volatility.

Chapter 4

Carry Trade Asset Allocation

4.1 Introduction

Setting up carry trade positions, which involve buying a high yielding currency and selling a low yielding currency, has produced positive excess returns in the past decades. Higher risk-adjusted returns can be achieved by creating more diversified portfolios which take long positions in a set of high yielding currencies and short positions in a set of low yielding currencies (see Rosenberg [2003]).

Rosenberg [2003] proposed a portfolio approach to carry trading which computes the portfolio positions by ranking the $G10$ currencies according to the value of the 1-month deposit interest rates. Cross-currency positions are initiated with 1-month forward contracts by buying the three highest yielding currencies and selling the three lowest yielding currencies. The backtesting results of this FX carry portfolio strategy generated a Sharpe ratio of 0.73 during the period from 1986 to 2003 (see Rosenberg [2003]). This carry trade strategy is also popular in the investment community. E.g., the *Deutsche Bank G10 Currency Harvest Index* replicates the performance of this strategy. The returns to the *Deutsche Bank G10 Currency Harvest Index* are tracked by an Exchange Traded Fund and thus tradeable by a wide range of investors (see also Section 3.1.2).

Vesilind [2006] analysed a similar framework for trading foreign exchange portfolios aimed at exploiting the forward rate bias. He implemented Rosenberg's approach on the $G10$ currencies on a data set ranging from 1993 to mid-2006, also rebalancing the portfolio at monthly intervals. The annualised Sharpe ratio of the portfolio was 0.94 and that of individual currency pairs ranged between 0.38 and 0.95. Vesilind [2006] noted, that more than half of the returns of the

carry portfolio were achieved by earning the interest rate differential. The other part of the portfolio returns came from profitable currency fluctuations. This can only be the case if, on average, the exchange rates moved in the opposite direction as predicted by UIP.

Vesilind [2006] also analysed a variation of this simple portfolio strategy which includes volatility as a risk factor. By computing carry-to-risk ratios, i.e., dividing the yield differential by the historical volatility for a set of 14 currency crosses, the model took a long position on the four currency crosses with the highest carry-to-risk ratios. The portfolio was rebalanced at a monthly frequency. The foreign exchange rate universe available to Vesilind's model was the USD exchange rate against the EUR, JPY, SEK, CAD, GBP, NOK, AUD, CHF, NZD and the EUR exchange rate against the JPY, SEK, GBP, NOK and CHF. The annualised Sharpe ratio of the carry portfolio was 1.53 and that of the individual currency pairs ranged between 0.60 and 1.67.

A model developed at *ABN AMRO* (see Mackel [2005]) also uses the risk-adjusted interest rate differential as an input to the formulation of a carry strategy. In this model, the 3-month deposit interest rate spread in two countries is divided by the 3-month actual volatility of the currency pair. The trade is initiated when the risk-adjusted carry is above its 2-year rolling average. The model signals are updated on a daily basis. The best Sharpe ratio of the strategy was 1.61 on the AUD/USD currency pair.

Taking the approach of including the volatility of currencies in the formulation of carry trading strategies one step further, correlations between currencies could provide an additional input to the asset allocation process of a carry strategy. Ellis and Jiltsov [2004] developed a foreign exchange carry portfolio based on a mean-variance optimisation algorithm. They calculate the variance-covariance (VCV) matrix historically and by exponential smoothing. On a portfolio backtest from 1987 to 2003 they report Sharpe ratios ranging between 0.64 and 0.87, depending on the methodology applied for the VCV matrix estimation.

Hochradl and Wagner [2010] extended the mean-variance approach by setting constraints on the maximum value-at-risk of the currency portfolio and allowing changes in the portfolio weights only in specific, discrete, amounts. Since the restrictions on the model mimic restrictions which portfolio managers face in practical currency management, the performance of this strategy should provide a good proxy for the returns generated by FX carry trading institutions. Hochradl and Wagner [2010] tested whether the limits to speculation LSH hypothesis for-

mulated by Lyons [2006] could have some relevance in explaining the enduring profitability of the FX carry trade. The LSH hypothesis states that when the exploitation of a known market inefficiency does not promise to deliver risk-adjusted returns over a specific threshold level, these inefficiencies could persist due to a lack of speculative arbitrage. Sarno et al. [2006] suggested a Sharpe ratio of 0.4 as the critical threshold which would need to be surpassed by a trading strategy in order for the LSH hypothesis to be rejected. Hochradl and Wagner [2010] showed that the FX carry strategy with realistic backtesting assumptions generated a Sharpe ratio of over 0.4 and thus conclude that in order to accept the LSH as a possible explanation for the persistence of carry trading profits, the Sharpe ratio threshold of 0.4 suggested by Sarno et al. [2006] would need to be increased.

4.2 Contributions

The research question we pose in this chapter is twofold.

Firstly, we would like to ascertain how diversification is beneficial to the performance of carry portfolios. To achieve this, we compare the performances of a set of simple scorecard-based and mean-variance optimised FX carry portfolios. While similar backtests have been performed in literature, a thorough comparison of these asset allocation methodologies on a homogeneous data set is, to date, missing. In order to ensure that these results are not too sensitive on the estimation of the VCV matrix, we perform portfolio backtests based on two different VCV estimators, i.e. a historical VCV matrix estimator and an exponentially-smoothed (*RiskMetrics*) VCV matrix estimator.

Secondly, we would like to assess whether alternative ranking criteria for the construction of scorecard-based currency portfolios are able to generate excess trading profits. We formulate two alternative ranking criteria which are closely related to the theme of carry trading.

Research by Chinn and Meredith [2005] has shown that the negative *beta* coefficient does not arise in the Fama-regressions (see Equation 4.2) when using long maturity bonds. These findings suggest that FX carry portfolios ranked by shorter maturity yields, should achieve better results than portfolios based on longer yield maturities. Since we would like to study this phenomenon in the context of currency speculation, the first alternative ranking criterion is to adopt yields of varying durations for the ranking of the G10 currencies. Specifically, we

will study the carry trading results of currency portfolios ranked by their 1-week, 1-month, 3-month, 2-year and 10-year yields.

The second alternative ranking criterion we consider is the momentum, or change, of the G10 currency yields. As discussed in Section 3.3.2, there is substantial evidence for large exposure to the FX carry trade by financial institutions. A change in the level of a yield in a specific currency denotes a change of carry-trade-attractiveness of this currency almost by construction. A lowering (heightening) of the interest rates should therefore be followed by sell (buy) pressure on the respective currency by carry traders, and a depreciation (appreciation) of the respective currency. We find indications for such buy/sell pressure by carry traders in research which relates changes in foreign exchange turnover to changes in measures of carry attractiveness for specific currencies (see Section 3.3.2). We will test portfolios aimed at exploiting these FX carry portfolio flows by ranking the G10 currencies by their respective yield momentum and taking equally weighted long (short) positions in the 3 currencies with the highest (lowest) ranks. Not knowing the precise carry strategies and rebalancing frequencies of all institutional carry traders, we examine the performance of such *carry-flows* portfolios based on the 1-week, 4-week, 8-week, 12-week, 26-week and 52-week momentum of the 2-year yields.

Pojarliev and Levich [2008] suggested that the return of FX managers should be benchmarked against the returns of four popular trading styles in the foreign exchange market (see Section 3.1.3). Since we focus on testing different methodologies for trading FX carry portfolios, we choose to utilise a simple proxy for the FX carry factor as the sole benchmark for our FX carry portfolio construction methodologies. We define our proxy for the FX carry trading-style by simulating the returns to a currency portfolio which takes equally weighted long positions in the three highest yielding $G10$ currencies against equally weighted short positions in the three lowest yielding currencies. The portfolio is rebalanced at a weekly frequency (see Appendix A, for a detailed description of the methodology and a performance analysis of the *Benchmark FX Carry Portfolio*).

Throughout this thesis we measure the relative FX carry trade outperformance (which we define as *carry-alpha*), as well as the exposure to the known FX carry factor (which we define as *carry-beta*) of the tested trading strategies. Similarly to popular factor models for modelling stock returns (see Fama and French [1992] and Carhart [1997]), we determine the loadings on the FX carry

factor and the relative outperformance by estimating a simple one factor model regressing the specific carry strategy returns on an intercept term and the returns of our *Benchmark FX Carry Portfolio* (see Section 4.4.4). We stress that the aim of our regressions is not to uncover risk factors which might contribute to explain the returns inherent to the FX carry trade itself. Instead, we address the question whether a simple implementation of the FX carry trade can be outperformed by more sophisticated methodologies, and thus whether there is room for professional currency managers to offer FX carry-related strategies at their habitual fees, considering the existence of low cost alternatives to gain exposure to *carry-beta*.

4.3   Data

4.3.1   The Currency Universe

Throughout this thesis we have chosen to analyse the FX carry trade on the *G10* currency universe, which is composed exclusively of currencies from developed economies.[1] At first this choice might seem arbitrary, since the *FRB* has been observed on a multitude of currencies including emerging market currencies. E.g. Bansal and Dahlquist [2000] and Flood and Rose [2002] have found statistically significant departures from *UIP* in emerging market currencies. Mayer [2009] analyses the performance of FX carry strategies in emerging market economies as well as developed economies. Using a dataset of 38 currencies Mayer [2009] shows how both classes of currencies exhibit significant speculation returns and thus discards the *limits to speculation hypothesis* (see Lyons [2006] and Section 4.1).

Nevertheless, there are reasons for concentrating the research focus on the *G10* currency basket. An important reason is given by the fact that the majority of studies in literature have been concerned with portfolios of currencies of developed countries (see Frankel and Poonawala [2006]). Also, the character of the carry returns of emerging market currency portfolios would merit a distinctively different treatment: Firstly, a speculator who buys emerging market currencies would find himself exposed to a different bouquet of risks and also a somewhat higher idiosyncracy of risks. For instance, emerging market countries might display very specific political and regulatory frameworks such as high default risks, political instability, capital controls or interest rate interventions.

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[1]See Section 2.2 for the components of the *G10* currency basket.

Secondly, implementational issues like data availability, lower liquidity and thus higher transactions costs, pose significant problems when directly comparing emerging market FX carry and developed markets FX carry strategies. These inherent differences seem to have a direct cause on the returns of the FX carry strategies. The different character of emerging market carry returns has been pointed out by Frankel and Poonawala [2006] who analysed the returns of carry trade portfolios of emerging market currencies. Frankel and Poonawala [2006] found that although the emerging market currencies are arguably riskier than developed market currencies, the bias in their forward rates, i.e. the potential return of trading FX carry portfolios, is smaller.

We note that future research should add to the scope of the following empirical studies by analysing similar methodologies on a broader currency universe.

4.3.2 G10 Foreign Exchange and Yields Data

Throughout this paper we will use foreign exchange spot rates, 1-week interest rates, 3-month interest rates, 2-year interest rates and 10-year year interest rates data for the G10 currencies. The data sources are *Bloomberg* and *Datastream* for the foreign exchange rates and the interest rates. The source for the 1-week interest rate data for Australia, New Zealand and Sweden are the respective central banks. The data set has a weekly frequency and spans the period from the 1st of January 1999 to the 5th of March 2010 (584 weekly observations). We also utilise gold spot rate data (as we later use gold as numeraire good) which we obtained from *Bloomberg*.

4.3.3 Yields Momentum Data

In order to simulate the currency portfolios tracking the portfolio flows of FX carry traders (see Section 4.2), we need to calculate the momentum, i.e. the change, of the yields for each currency in the G10 universe. The momentum time series are computed according to:

$$YD.MOM_t^{C,d}(l) = i_t^{C,d} - i_{t-l}^{C,d} \qquad (4.1)$$

Where $YD.MOM_t^{C,d}(l)$ denotes the yield-momentum for the currency C with momentum-length l in time period t and $i_t^{C,d}$ denotes the yield for currency C in period t. The duration of the yields is denoted by d. In our computations we will

utilise $d = 2$ (i.e. we compute the momentum of the 2-Year yields).

In the empirical section, we will test FX carry portfolios with different parameters for the momentum lag l, and thus compute the yield momentum time series for $l = 1, 4, 8, 12, 26, 52$.

4.3.4 Fama Regressions

To gain a better understanding of our data set, we estimate the Fama regression (see Section 3.2.3), which allows us to test for the validity of the UIP within our data set:

$$\Delta_k s_{t+k} = \alpha + \beta(FD_{t,k}) + \epsilon_{t+k} \tag{4.2}$$

where $\Delta_k s_{t+k} = log(S_{t+k}) - log(S_t)$, and $FD_{t,k} = i_{t,k} - i^*_{t,k}$.

For UIP to hold, the β coefficient should assume a value of unity. If β is zero, the exchange rate follows a random walk. We perform a two-sided statistical test with the following hypotheses:

$$H_0: \qquad \beta = 0 \qquad \text{(random walk)} \tag{4.3}$$

$$H_1: \qquad |\beta| > 0 \qquad \text{(no random walk)} \tag{4.4}$$

The Fama-regressions are estimated for the G10 exchange rates against the Euro on the whole data sample from the 1st of January 1999 to the 5th of March 2010. In addition, we split the data set into two subsamples which are used to examine the stability of the coefficients and their behaviour during the recent credit crisis. The first data subsample begins on the 1st of January 1999 and ends on the 29th of December 2006, the second data subsample begins on the 5th of January 2007 and ends on the 5th of March 2010.

The regression results for the whole data set exhibit a negative β coefficient in 6 out of 9 cases (see Table 4.1). Only the EUR/AUD, EUR/NZD and EUR/JPY currency crosses exhibited positive β coefficients. In no instance the null hypothesis of the exchange rate following a random-walk could be discarded at a statistically significant level.

In the first data subsample the forward rate bias is even stronger since only 2 out of 9 exchange rates exhibit a positive β coefficient (see Table 4.2). The

negative β coefficient on the EUR/CHF currency cross was even statistically significant (p-value of 0.02). On average, on these two data samples the forward discount predicted the exchange rate change in the wrong direction.

Interestingly these results change dramatically when we consider the most recent data sample which coincides with the credit crisis. In this case, most of the *beta* coefficients were positive and over unity (see Table 4.3). Albeit a statistically significant positive β could only be found in the case of EUR/NZD, we note that there has been a tendency for the forward discount to underestimate the subsequent exchange rate changes during the credit crisis.

Our results are in line with previous academic research which finds that the forward premium systematically predicts changes in the spot exchange rate in the wrong direction (see Section 3.2.3). From these results we would intuitively expect carry trading strategies to be profitable within the whole data set, and that the period of the credit crisis should produce worse carry trading performances than the first data subsample.

Currency Pair	α	$Pr(> |t_\alpha|)$	β	$Pr(> |t_\beta|)$
EUR/USD	-4e-04	0.49	-2.41	0.22
EUR/JPY	-1e-04	0.95	0.46	0.89
EUR/GBP	-0.0016	0.08	-4.36	0.13
EUR/CHF	0.0015	0.06	-4.37	0.08
EUR/CAD	1e-04	0.91	-4.35	0.21
EUR/AUD	9e-04	0.62	1.17	0.77
EUR/NZD	0.0034	0.06	5.47	0.06
EUR/NOK	1e-04	0.89	-0.25	0.86
EUR/SEK	-1e-04	0.8	-3.44	0.37

Table 4.1: Fama Regression Results for the Data Set from the 1st of January 1999 to the 5th of March 2010.

Currency Pair	α	$Pr(> |t_\alpha|)$	β	$Pr(> |t_\beta|)$
EUR/USD	-7e-04	0.29	-4.43	0.04
EUR/JPY	5e-04	0.84	-1.68	0.71
EUR/GBP	-0.0012	0.27	-4.09	0.19
EUR/CHF	0.0023	0.03	-7.27	0.02
EUR/CAD	-4e-04	0.58	-6.66	0.09
EUR/AUD	5e-04	0.79	0.33	0.93
EUR/NZD	0.0019	0.29	2.75	0.35
EUR/NOK	-2e-04	0.79	-0.93	0.47
EUR/SEK	0	0.95	-3.85	0.23

Table 4.2: Fama Regression Results for the Data Set from the 1st of January 1999 to the 29th of December 2006.

Currency Pair	α	$Pr(> |t_\alpha|)$	β	$Pr(> |t_\beta|)$
EUR/USD	-4e-04	0.71	5.48	0.27
EUR/JPY	-5e-04	0.89	4.39	0.49
EUR/GBP	-0.0016	0.37	0.92	0.91
EUR/CHF	0.001	0.49	-1.53	0.74
EUR/CAD	5e-04	0.7	1.23	0.91
EUR/AUD	0.0092	0.37	16.51	0.39
EUR/NZD	0.0126	0.03	19.46	0.02
EUR/NOK	0.0035	0.16	12.45	0.14
EUR/SEK	-4e-04	0.7	1.24	0.94

Table 4.3: Fama Regression Results for the Data Set from the 1st of January 2007 to the 5th of March 2010.

4.4 Methodology

In the following we will outline the simple and optimised asset allocation methodologies for constructing FX carry portfolios (Section 4.4.1 and Section 4.4.2). The historical and RiskMetrics estimators for the variance-covariance matrix will be outlined in Section 4.4.3. Finally, we will introduce statistical regressions for determining the potential of the asset allocation algorithms to generate *carry-alpha* (Section 4.4.4).

4.4.1 Simple Scorecard-based Asset Allocation

As described by Rosenberg [2003], the simple scorecard-based asset allocation algorithm assumes long and short positions in currencies based on the ranking of specific variables associated with the currencies. In the case of a standard FX carry portfolio, these variables would be interest rates of the same maturity for each currency.

After ranking the currencies based on the variable of choice, the algorithm takes long positions in the highest-ranked N currencies and short positions in the lowest-ranked N currencies (see Rosenberg [2003]). The portfolio weights of the resulting N cross-currency positions are equally weighted with $w = \frac{1}{N}$. In the following section equally weighted carry portfolio strategies are tested for $N = 1, 2, 3, 4$.

4.4.2 Mean-Variance Optimised Asset Allocation

The basic assumption behind the mean-variance optimised currency portfolios is that exchange rates follow a random walk (see Hochradl and Wagner [2010], Ellis and Jiltsov [2004]). This assumption is in line with academic literature which

finds that the best model for explaining exchange rate movements is indeed the random-walk model (see Meese and Rogoff [1983a] and Meese and Rogoff [1983b]). The random walk model for the log-levels is given by Equation 4.5:

$$s_{t+k} = s_t + \epsilon_{t+k} \tag{4.5}$$

Where ϵ_{t+k} is a disturbance term with $E[\epsilon_{t+k}] = 0$. The expected exchange rate in k periods would then be:

$$s_{t+k}^e = s_t \tag{4.6}$$

Using Equation 4.6 and equation Equation 3.1, the expected excess return of a foreign exchange position under the random walk assumption is the interest rate differential between the foreign currency and the home currency (see Equation 4.7).

$$r_{t+k}^e = s_{t+k}^e - s_t - \left(i_{t,k} - i_{t,k}^*\right) \tag{4.7}$$
$$= i_{t,k}^* - i_{t,k} \tag{4.8}$$

Following these assumptions, for a euro-based investor, the expected return of each single currency is thus given by its interest rate differential to the Euro. In our G10 currency portfolios the vector of expected returns $\mathbf{r}^e$ is a (10×1) vector composed of the interest rate differential for each G10 currency to the Euro:

$$
\mathbf{r}^e = \begin{pmatrix} r_{EUR}^e \\ r_{USD}^e \\ r_{JPY}^e \\ r_{GBP}^e \\ r_{CHF}^e \\ r_{CAD}^e \\ r_{AUD}^e \\ r_{NZD}^e \\ r_{NOK}^e \\ r_{SEK}^e \end{pmatrix} = \begin{pmatrix} i_{EUR} - i_{EUR} \\ i_{USD} - i_{EUR} \\ i_{JPY} - i_{EUR} \\ i_{GBP} - i_{EUR} \\ i_{CHF} - i_{EUR} \\ i_{CAD} - i_{EUR} \\ i_{AUD} - i_{EUR} \\ i_{NZD} - i_{EUR} \\ i_{NOK} - i_{EUR} \\ i_{SEK} - i_{EUR} \end{pmatrix} \tag{4.9}
$$

For a given set of portfolio weights $\mathbf{w}_P$, also a (10×1) vector, the expected return of the portfolio r_P can be computed according to Equation 4.10.

$$r_P = \mathbf{w}^T \mathbf{r}^e \tag{4.10}$$

The expected volatility of a portfolio of assets can be computed by Equation 4.11.

$$\sigma_P^2 = \mathbf{w}^T \boldsymbol{\Sigma}_{rr} \mathbf{w} \tag{4.11}$$

Where $\boldsymbol{\Sigma}_{rr}$ is the estimated variance-covariance matrix (10×10) of the returns of the G10 currencies quoted against an auxiliary numeraire good (i.e. gold). We introduced gold as a numeraire, in order to more elegantly align currency performances with the yields in all 10 economies of the *G10* currency basket. Moreover, the introduction of the numeraire allows us to impose homogeneous restrictions on all currencies, as long as the restriction of $\mathbf{w}^T \mathbf{1} = 0$ holds. This restriction ensures that the performance of the numeraire does not affect the performance of the FX carry portfolios. If the portfolios were backtested against a base currency, the sum of the weights would correspond to the negative exposure of the base currency. In order to treat that base currency like the other 9 currencies at least two restrictions specifying the upper and the lower bounds of the sum of the weights (i.e. of the negative exposure to the base currency) would need to be set, which is arguably a less elegant solution.

The mean-variance portfolio selection algorithm computes the optimal vector of weights $\mathbf{w}_P^*$ for a currency portfolio, s.t. the portfolio variance is minimised given a specific level of portfolio return. Since minimising portfolio variance is equivalent to minimising the portfolio standard deviation, the algorithm is effectively maximising the Sharpe ratio of the portfolio. We impose an additional restriction on the portfolio weights, which states that the sum of the portfolio weights has to net out to zero. This restriction ensures the typical self-financing character of foreign exchange positions, since the exposure to the auxiliary numeraire good gold is set to null. This portfolio selection problem can be expressed mathematically as:

$$\min_{\mathbf{w}} \quad \sigma_P^2 = \mathbf{w}^T \boldsymbol{\Sigma}_{rr} \mathbf{w} \quad , \tag{4.12}$$

s.t.

$$r_P = \mathbf{w}^T \mathbf{r}^e = \tilde{r} \quad , \tag{4.13}$$

and

$$\mathbf{w}^T\mathbf{1} = 0. \tag{4.14}$$

We calculate the solution via a quadratic programming solver, as implemented by Würtz et al. [2009].

We set $\tilde{r}$ to an arbitrary small and positive value. The value of $\tilde{r}$ in each period t is set at one tenth the value of the accrued carry of the simple *G10* FX carry portfolio with 3 long and 3 short positions. Now, given this target return the weights are calculated such that the portfolio variance is minimised according to Equation 4.12, s.t. Equation 4.13 and Equation 4.14 hold. This is equivalent to maximising the Sharpe ratio for that given level of return is maximised. The portfolio weights are subsequently rescaled in order to achieve constant long and short exposures of 1 (i.e. 100 percent of capital).

Discusion of the Mean-Variance Approach in this Context   Although the mean-variance optimisation techniques implemented by Hochradl and Wagner [2010] and Ellis and Jiltsov [2004] to optimise FX carry portfolios offer a simple framework to address the question of how to best diversify carry portfolios, they do also entail several drawbacks when used for practical portfolio management. Most prominently, important caveats of the mean-variance methodology are: High sensitivity to estimation error in the input parameters (see e.g. Black and Litterman [1992], Michaud [1989]), the fact that the distributional assumption does not match stylized facts of financial returns (see e.g. Jondeau and Rockinger [2005], Cont [2001]), the objective function which is arguably inappropriate (see e.g. Scott and Horvath [1980] and Bernartzi and Thaler [1995]) and the assumption of a single period model is not realistic (see e.g. Rotando and Thorp [1992]).

Michaud [1989] noted that wrong estimation of the models inputs (μ and σ) leads to suboptimal portfolio allocations, and called mean-variance optimisers *error-maximisers*. Following Jorion [1986], unconstrained mean-variance portfolios tend to strongly overweight assets with high expected returns. Michaud [1989] postulated, that especially those assets with the highest expected returns exhibit large estimation errors. While also the variance-covariance matrix constitutes a source of estimation error, its impact on the result of the mean variance optimisation is somewhat smaller than the effect of errors in the expected returns vector (see Chopra and Ziemba [1993]).

The predictability of stock market returns has been a challenge to market practitioners and financial economists for a long time. While numerous studies have proposed successful financial forecasting methodologies [2], other studies question these results (see e.g. Nelson and Kim [1993] and Staumbaugh [1999]) and raise doubts on the evidence of predictability of financial returns, since out-of-sample forecasts have often performed worse than a random walk model (see Meese and Rogoff [1983a]). Thus, most attempts to predict returns fail to disprove the Efficient Market Hytpothesis *EMH*.[3] As Michaud [1989] stated though, errors in the estimation of the means will significantly distort the output of the mean-variance optimisation. A possible remedy to this problem is to completely renounce to the need of formulating the expected returns as input to the optimisation process altogether, by e.g. computing minimum variance portfolios which require only the variance-covariance matrix as an input (see Amenc and Martellini [2002]). An alternative solution to this problem is provided by the Black-Litterman methodology. The Black-Litterman methodology reduces the impact of erroneous return estimates on the returns vector by setting a stable prior which is then updated with individual return forecast while accounting for estimation errors within these (see Black and Litterman [1992]).

In our empirical research, we only implicitly estimate FX returns by setting the expected return on a currency position equal to its interest rate. This is de facto equivalent to assuming a random walk for the FX spot rates, an empirical observation well documented throughout the *UIP* and *FRB* literature (see Section 3.2.3). These return estimates offer intertemporaly stable estimations, resulting in smooth portfolio weights, reducing turnover and therefore keeping transactions costs low.

The second essential input to mean variance optimisation consists of the variance-covariance matrix σ. Difficulties in the estimation of this input include the curse of dimensionality when estimating model parameters and the danger of getting non-positive semi-definite matrices (see e.g. Engle [2002]). As the number of assets increases, the number of parameters which have to be estimated increases at least quadratically (see Engle and Sheppard [2009]). Numerous ap-

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[2]See e.g. Dempster and Jones [2001], Lyons [2006], Zimmermann et al. [2006] and Dunis et al. [2010], just to name a few.

[3]The *EMH* states that in an efficient financial market it is not possible to predict financial returns with any satisfactory degree of accuracy, since all relevant information is immedeately reflected in the price of the assets (see also Section 3.2.1).

proaches for addressing these problems have been proposed in literature.[4] A good overview on the methodologies is provided by e.g. Engle and Sheppard [2009], Engle and Kroner [1995] and Palandri [2009].

While some studies find economical value in optimizing portfolios with more complex estimators for the VCV matrix (see Engle and Sheppard [2009]), others find that the additional complexity associated with selecting and estimating a specific multivariate VCV estimator is not remunerated by significantly enhanced statistical and economic performance. West and Cho [1999] found that GARCH models did not significantly outperform the equally weighted standard deviation estimates in out-of-sample forecasts, except for very short time horizons. The *RiskMetrics* technical document (see Zangari and Longerstaey [1996]) demonstrates that the dynamics of the exponential model's forecasts closely mimic those produced by the GARCH(1,1) model. Suganuma [2000] applies White's Bootstrap Reality Check (see White [2000]) to the problem of selecting the best volatility model, testing rolling window, EWMA, GARCH and stochastic volatility models and finds that no model consistently outperforms the benchmark methodology defined as the exponentially weighted moving average *EWMA* with decay factor $\lambda = 0.94$ for daily returns.

For our practical investigation of FX carry portfolios we thus decide to limit our tests to two naive VCV matrix estimators, namely the simple historical VCV estimator and the *EWMA RiskMetrics* estimator, which we will outline in the following section.

4.4.3   Variance-Covariance Matrix Estimators

Having a clearly defined vector of expected returns for the mean-variance optimisation (see Equation 4.9), the question arises whether the estimation methodology of the variance-covariance matrix has a substantial effect on the profitability of the optimised carry trading portfolios.

The variance-covariance matrix at time t, $\boldsymbol{\Sigma}_{rr,t}$, is composed of all variances $\sigma^2_{ii,t}$ and covariances $\sigma^2_{ij,t}$ of returns of the n (in our case $n = 10$) currencies in the carry portfolio versus gold:

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[4]E.g. Constant Conditional Correlations and Dynamical Conditional Correlations (see Engle [2002]), Orthogonal GARCH (see Alexander [2000]), BEKK (see Engle and Kroner [1995])

$$\mathbf{\Sigma}_{rr,t} = \begin{pmatrix} \sigma_{11,t}^2 & \sigma_{12,t}^2 & \cdots & \sigma_{1n,t}^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1,t}^2 & \sigma_{n2,t}^2 & \cdots & \sigma_{nn,t}^2 \end{pmatrix} \quad (4.15)$$

We examine the performance of mean-variance optimised carry portfolios based on two different methodologies for the estimation of the variance-covariance matrix. These methodologies are historical VCV matrix estimation, and exponential smoothing VCV matrix estimation as advocated by Zangari and Longerstaey [1996]. Both methodologies are briefly outlined below. We maintain the assumption of the exchange rate following a random walk, thus the mean return can be omitted from the traditional formulas for the calculation of the variances and covariances.

The estimation of both VCV matrices is performed on a rolling basis with a fixed starting point on the 16th of January 1998. The first available data window starts on the 16th of January 1998 and ends on the 1st of January 1999 (50 weekly observations). This data window is sequentially expanded in order to include all available data on each estimation date.

Historical Variance-Covariance Matrix   The historical estimation of the variance σ_{ii}^2 of the returns r of a currency i is calculated according to the following formula:

$$\sigma_{ii(t+1|t,n)}^2 = \frac{1}{n-1} \sum_{k=0}^{n-1} r_{i(t-k)}^2 \quad (4.16)$$

The variances of all currencies in the currency portfolio lie on the diagonal of the variance-covariance matrix. The off-diagonal elements, which correspond to the covariances between the returns of two currencies, are calculated according to Equation 4.17.

$$\sigma_{ij(t+1|t,n)}^2 = \frac{1}{n-1} \sum_{k=0}^{n-1} r_{i(t-k)} r_{j(t-k)} \quad (4.17)$$

Conditional Variance-Covariance Matrix: *RiskMetrics* Exponential Smoothing   A further simple forecasting method which can be applied for the estimation of the variances and covariances is exponential smoothing. Exponential smoothing models can be seen as a special case of the GARCH model of

Bollerslev [1986] with a pre-determined smoothing parameter α. Volatility is then estimated using the following formula:

$$\sigma^2_{ij(t+1|t,\alpha)} = \alpha\sigma^2_{(t|t-1)} + (1-\alpha)\left(r_{i,t}r_{j,t}\right) \tag{4.18}$$

High values of α would generate a more responsive and rougher behaviour in the volatility estimate and low values of α give less responsive and smoother volatility estimates. As suggested by Zangari and Longerstaey [1996], we set the smoothing parameter α to 0.97.

4.4.4 Statistical Test for Carry-Alpha

After simulating the performance of the currency portfolios, we test whether they exhibit a statistically significant ability to generate *carry-alpha* (see Section 4.2). Following recent research on FX hedge funds performance attribution (see Pojarliev and Levich [2008]), we estimate a factor model of the form:

$$R_t = \alpha + \beta F_t + \epsilon_t \tag{4.19}$$

where R_t is the excess return generated by the relevant currency portfolio strategy, F_t is the return generated by the *Benchmark FX Carry Portfolio*, β is a coefficient or factor loading that measures the sensitivity of the strategy returns to the FX carry benchmark, α is a measure of return associated purely to the specific portfolio strategy and ϵ is a random error term. Statistically significant positive values of the α-intercept would signal the potential of the specific asset allocation methodology to outperform the FX carry benchmark.

The returns to the *Benchmark FX Carry Portfolio* F_t are computed by simulating the returns of a currency portfolio based on the allocation algorithm of the Currency Harvest Index by Deutsche Bank (see Section 3.1.2). In Appendix A we discuss the methodology and performance of our *Benchmark FX Carry Portfolio* in more detail.

4.5   Empirical Results

4.5.1   Discussion of the FX Carry Portfolio Asset Allocation Performances

In this chapter we simulated the trading performance of three classes of $G10$ currency portfolios aimed at trading the FX carry theme. With the first set of currency portfolios we examine the performance of different asset allocation methodologies for implementing FX carry portfolios. With the second set of currency portfolios we will analyse the results of selecting the currencies according to yields of different durations. Finally, the third set of currency portfolios is constructed in order to follow the portfolio flows of FX carry traders.

Table 4.4 summarises performance metrics and return attribution measures for the three different classes of currency portfolios. The first column of Table 4.4 describes the criterion after which the G10 currencies are ranked (see Section 4.4.1). In the case of the optimised asset allocation strategies, the 'Criterion'-column represents the source for the vector of expected returns (see Section 4.4.2). The second column ('Allocation') of Table 4.4 describes the utilised asset allocation methodology (i.e. simple or optimised). In the third and fourth columns the annualised arithmetic return r^a and the Sharpe ratio SR are listed for each currency portfolio. The last three columns of Table 4.4 allow to identify the source of the strategy total returns listed in the r^a-column: r^a_{FX} represents the annualised arithmetic returns generated from FX movements, r^a_{YD} the annualised arithmetic return generated from yield pickup and r^a_{TC} represent the annualised transactions costs in percent.

Figure 4.1 depicts the cumulative performances of the three classes of currency portfolios related to the FX carry trade. Table 4.5 summarises the regression results of the factor model testing for the ability of the portfolio algorithms to outperform the FX carry trade proxy.

In the following we will discuss the empirical results of backtesting these three classes of currency portfolios.

1st Set of FX Portfolios: Asset Allocation Algorithms   A key result which emerges from the asset allocation backtests is that FX carry portfolios benefit from portfolio diversification. This becomes evident when looking at the Sharpe ratios of the different strategies in Table 4.4: The simple strategy with

PANEL A
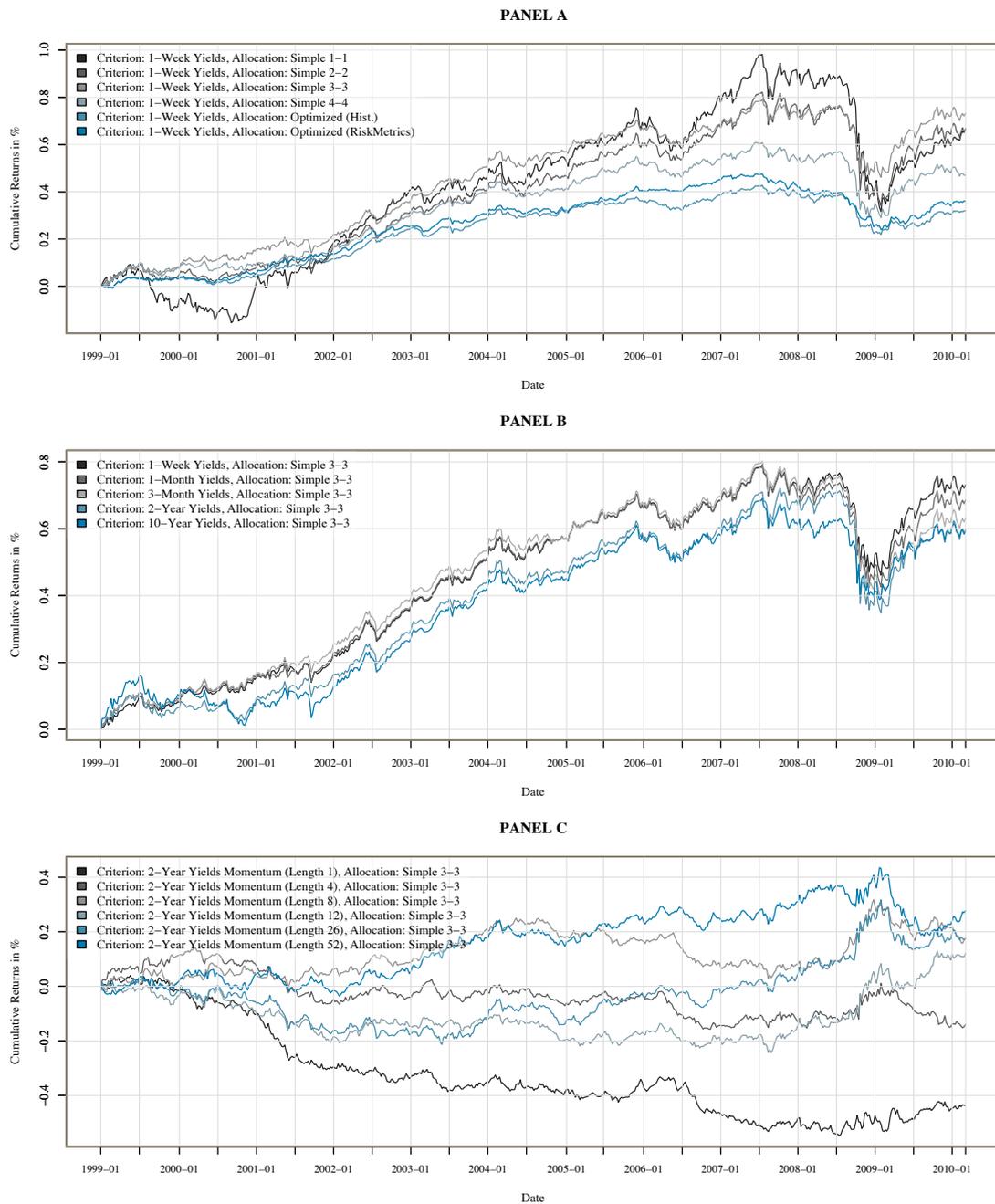
PANEL B

PANEL C

Figure 4.1: Cumulative Returns of the Asset Allocation Models based on the FX Carry Trade (PANEL A: Different Asset Allocation Algorithms; PANEL B: Varying Yield Durations as Allocation Criteria; PANEL C: 2-Year Yield Momentum as Allocation Criteria)

Criterion	Allocation	r^a	SR	r^a_{FX}	r^a_{YD}	r^a_{TC}
1-Week Yields	Simple 1-1	0.0593	0.38	0.0009	0.0630	-0.0047
1-Week Yields	Simple 2-2	0.0595	0.49	0.0109	0.0517	-0.0031
1-Week Yields	Simple 3-3	0.0651	0.67	0.0255	0.0426	-0.0030
1-Week Yields	Simple 4-4	0.0419	0.52	0.0105	0.0349	-0.0035
1-Week Yields	Opt. (Hist.)	0.0284	0.61	0.0052	0.0283	-0.0051
1-Week Yields	Opt. (RiskM.)	0.0320	0.73	0.0104	0.0282	-0.0066
1-Week Yields	Simple 3-3	0.0651	0.67	0.0255	0.0426	-0.0030
1-Month Yields	Simple 3-3	0.0610	0.64	0.0206	0.0426	-0.0021
3-Month Yields	Simple 3-3	0.0561	0.60	0.0158	0.0424	-0.0020
2-Year Yields	Simple 3-3	0.0532	0.51	0.0148	0.0418	-0.0033
10-Year Yields	Simple 3-3	0.0526	0.53	0.0162	0.0402	-0.0037
Yields Mom. (1)	Simple 3-3	-0.0389	-0.57	0.0314	-0.0021	-0.0681
Yields Mom. (4)	Simple 3-3	-0.0125	-0.17	0.0262	-0.0021	-0.0365
Yields Mom. (8)	Simple 3-3	0.0154	0.19	0.0426	-0.0019	-0.0253
Yields Mom. (12)	Simple 3-3	0.0108	0.14	0.0320	-0.0011	-0.0201
Yields Mom. (26)	Simple 3-3	0.0157	0.18	0.0280	0.0010	-0.0133
Yields Mom. (52)	Simple 3-3	0.0247	0.29	0.0291	0.0048	-0.0092

Table 4.4: Performance Metrics of the Asset Allocation Models for FX Carry Portfolios (r^a: Annualised Arithmetic Return, SR: Sharpe Ratio, r^a_{FX}: Annualised Return from FX Movements, r^a_{YD}: Annualised Return from Yield Differentials, r^a_{TC}: Annualised Return from Transactions Costs)

Criterion	Allocation	α	$Pr(> |t_\alpha|)$	β	$Pr(> |t_\beta|)$
1-Week Yields	Simple 1-1	-0.0004	0.4439	1.26	0.0000
1-Week Yields	Simple 2-2	-0.0003	0.1883	1.18	0.0000
1-Week Yields	Simple 3-3	-0.0000	1.0000	1.00	0.0000
1-Week Yields	Simple 4-4	-0.0002	0.2126	0.79	0.0000
1-Week Yields	Opt. (Hist.)	0.0001	0.5047	0.33	0.0000
1-Week Yields	Opt. (RiskM.)	0.0003	0.1448	0.24	0.0000
1-Week Yields	Simple 3-3	-0.0000	1.0000	1.00	0.0000
1-Month Yields	Simple 3-3	-0.0000	0.5838	0.97	0.0000
3-Month Yields	Simple 3-3	-0.0001	0.4366	0.94	0.0000
2-Year Yields	Simple 3-3	-0.0003	0.0908	1.03	0.0000
10-Year Yields	Simple 3-3	-0.0002	0.4656	0.94	0.0000
Yields Mom. (1)	Simple 3-3	-0.0007	0.0722	-0.03	0.3221
Yields Mom. (4)	Simple 3-3	-0.0001	0.8645	-0.14	0.0000
Yields Mom. (8)	Simple 3-3	0.0005	0.2249	-0.19	0.0000
Yields Mom. (12)	Simple 3-3	0.0004	0.3612	-0.16	0.0000
Yields Mom. (26)	Simple 3-3	0.0006	0.2360	-0.22	0.0000
Yields Mom. (52)	Simple 3-3	0.0008	0.1135	-0.22	0.0000

Table 4.5: Regression Results for the Factor Model $R_t = \alpha + \beta F_t + \epsilon_t$ (F_t = Benchmark FX Carry Portfolio Returns, R_t = Portfolio Returns of the Carry Trade Asset Allocation Strategies).

one long and one short position generates a Sharpe ratio of 0.38; the more diversified simple strategy with three long and three short positions generates a higher Sharpe ratio of 0.67. An explanation for the better risk-adjusted performance of the more diversified strategies can be found in Table 4.4. Whereas the least diversified simple carry portfolios with one and two long and short positions generate the highest yield pickup (cumulative 6.30% *per annum* and 5.17% *per annum*), their profits from FX movements are relatively small (cumulative 0.09%

per annum and 1.09% *per annum*). The higher FX returns generated by the more diversified strategies compensate for the lower pickup in yield of these strategies. In addition, the returns of the more diversified carry strategies exhibit a lower volatility of returns, which is the principal reason behind the higher Sharpe ratios of these strategies.

A second noteworthy result is that the simple, equally weighted carry portfolios, exhibit higher annualised returns than the optimised carry portfolios. While the simple strategies generate annualised returns of around 4% *per annum* to 6.5% *per annum*, the returns of the optimised portfolios are around 3% *per annum* (see Table 4.4). Nevertheless, the two optimised strategies generate higher Sharpe ratios (Sharpe ratios of respectively 0.61 and 0.73) than most of the simple, equally weighted strategies. Only the simple strategy with three long and three short positions (Sharpe ratio of 0.67) generated a comparable result (see table Table 4.4).

On the other hand, the results also reveal a negative feature of the optimised FX carry asset allocation methodologies since they generate higher transactions costs than the simple carry portfolios (see Table 4.4). These transactions costs originate in the higher rebalancing frequency inherent to the optimised asset allocation algorithms.

The results for the regressions testing for the ability of the different asset allocation algorithms to generate *carry-alpha* are summarised in Table 4.5. The regressions show that no asset allocation methodology was able to generate *carry-alpha* at a statistically significant level, when compared to the benchmark carry portfolio strategy (see Appendix A). Notably, the *RiskMetrics*-optimised carry portfolio strategy was able to produce returns which were unrelated to the *carry-beta*, but the intercept could not be regarded statistically significantly different from zero at a lower confidence level than 14.48%.

2nd Set of FX Portfolios: Alternative Yield Maturities In Table 4.4 a general pattern can be recognised for the second set of currency portfolios: The shorter the yields used for the ranking of the currencies in the simple asset allocation methodology, the better the FX carry portfolio performance. The portfolios with the shorter yields as allocation criteria exhibit larger annualised returns r^a, as well as higher Sharpe ratios SR. While the portfolio with the shortest maturity yields as ranking criterion generated a Sharpe ratio of 0.67,

the currency portfolio with the longest maturity yields as allocation criterion generated a lower Sharpe ratio of 0.53.

Since the return generated by the carry component r_{YD}^a is fairly constant in all six portfolios of this group, the better performance of the portfolios based on the shorter maturity yields can be attributed the returns generated by the FX component r_{FX}^a (see Table 4.4).

The regressions testing for *carry-alpha* reveal that disregarding the maturity of the yields used for the portfolio construction, the returns are correlated to the FX carry benchmark; all *beta's* are close to unity and highly statistically significant (see Table 4.5). Also in this case, no portfolio could generate *investment-style-alpha* at a statistically significant level.

3rd Set of FX Portfolios: Trading Carry Portfolio Flows The third set of currency portfolios is computed according to the simple scorecard based asset allocation methodology described in Section 4.4.1. The allocation criterion consists in the momentum of the 2-Year yields (see Section 4.3.3) for each of the currencies in the portfolio. We compare the performance of different lag lengths for computing the 2-Year yields momentum. The different lag lengths are: 1 (1-Week yield change), 4 (1-Month yield change), 8 (2-Month yield change), 12 (3-Month yield change), 26 ($\frac{1}{2}$-Year yield change) and 52 (1-Year yield change).

Figure 4.1 reveals the general tendency, that the performance of the currency portfolios increases as the lags for compting the yield momentum rise. The performance metrics in Table 4.4 confirm this intuition: The annualised returns r^a exhibit their lowest value of -3.89% *per annum* in the 1-week yield momentum portfolio and their highest value of 2.47% *per annum* in the 52-week yield momentum portfolio. The Sharpe ratios SR behave analogously, since they exhibit their lowest value of -0.057 in the 1-week yield momentum portfolio and their highest value of 0.29 in the 52-week yield momentum portfolio.

When we observe the source of the returns to the *carry-flows* portfolios in Table 4.4, we gain further insight into the source of the profits associated to these portfolios. The *carry-flows* portfolio profits tend to derive mainly from FX movements while there is no relevant yield pickup associated with these portfolios. All *carry-flows* portfolios generate returns from the currency fluctuations r_{FX}^a ranging between 2.91% *per annum* and 4.26% *per annum*, while their carry return ranges only between -0.21% *per annum* and 0.48% *per annum*. The gener-

ated transactions costs r^a_{TC} generated by implementing these portfolio strategies are relatively high (0.92% *per annum* - 6.81% *per annum*) and rise as the lag length for the computation of the yield momentum criterion shortens. In all six yield-momentum based currency portfolios, the transactions costs significantly influence the overall profitability of the asset allocation strategy.

The regression tests for *carry-alpha* are summarised in Table 4.5. A further important feature of the portfolios aimed at exploiting the portfolio flows of carry traders is the negative *beta* they exhibit to the carry trade benchmark (the *beta* values range from −0.03 to −0.22 in this group of FX portfolios). Also in this case the portfolios do not exhibit statistically significant ability for *carry-alpha* generation. We note that this may be due solely to the effect of the high transactions costs since the p-values decrease with the length of the carry-momentum, reaching a low value of 0.11 in the case of the portfolios based on the 52-week yield change.

4.5.2 Additional Considerations

Comprehensive Risk-Adjustments

The portfolios presented in this chapter aim at improving the performance of the *G10* FX carry trade by alternative asset allocation techniques. Thus, the appropriate benchmark for our approaches is the performance of a simple FX carry portfolio. As we discussed in Section 3.1.2, a good number of risk factors other than carry have been proposed for the FX markets. These other risk factors are: value, momentum and volatility. Considering these additional risk factors, the question arises whether our FX carry portfolios are outperforming the vanilla returns because they are loading on some risk factors and thus earning a risk premium to do so. In order to evaluate this possibility, we have performed additional factor-regressions for two representative strategies, namely the *RiskMetrics* optimised FX carry portfolio and the *frontrunning* FX carry portfolio with a lag parameter of 52. For each portfolio we have performed regressions on three distinct data-ranges, namely the full data-range (January 1999 - March 2010), a *pre-crisis* data-range (January 1999 - May 2007) and a *post-crisis* data-range (June 2007 - March 2010).

The regression results for the *RiskMetrics* optimised portfolio are summarised in Table 4.6 - Table 4.8. The regression results for the representative *frontrunning* portfolio are summarised in Table 4.9 - Table 4.11.

We now analyse the risk-adjustment regression results for the *RiskMetrics* FX carry portfolio. As expected the carry-beta factor is positive and highly statistically significant throughout all three data-ranges. Surprisingly though, other significant risk-factor loadings can be observed. Throughout all three data-ranges also the value-beta is significantly positive. Additionally, on the *pre-crisis* data-range the momentum risk-factor exhibits a statistically significant negative coefficient. Except on the *pre-crisis* sample the *alpha*-intercept is negligibly small, signifying that the *RiskMetrics* optimised FX carry portfolio is not able to produce superior returns, when adjusted for common risk factors in the FX markets.

Similar to the results presented in Section 4.5.1, the comprehensive risk-adjustment regressions for the *frontrunning* portfolio with a lag parameter of 52 (Table 4.9 - Table 4.11) display a negative loading on the carry-coefficient. Some of the positive loading that we observed in Table 4.5 on the *alpha*-intercept is now taken over by the risk-factors *value* and *momentum*: the *momentum* factor receives significantly positive factor loadings in the *full* and *post-crisis* data-ranges; the *value* factor receives a significantly positive loading in the *pre-crisis* data-range and a significantly negative loading in the *post-crisis* data-range.

The results in this section thus outline that the alpha that could be obtained by optimising the asset allocation of FX carry portfolios is eroded when comprehensive risk adjustments are being performed. Thus, by optimising the FX carry strategy we have effectively loaded on other risk factors.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.36	0.17
Carry	0.27	0.02	14.22	0.00
Momentum	-0.03	0.02	-1.57	0.12
Value	0.09	0.01	6.45	0.00
Volatility	-0.03	0.04	-0.81	0.42

Table 4.6: Comprehensive Risk-adjustment regression for the *RiskMetrics* optimised FX carry portfolio (January 1999 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	2.44	0.01
Carry	0.42	0.03	13.38	0.00
Momentum	-0.13	0.02	-5.32	0.00
Value	0.08	0.02	3.95	0.00
Volatility	-0.07	0.05	-1.40	0.16

Table 4.7: Comprehensive Risk-adjustment regression for the *RiskMetrics* optimised FX carry portfolio (January 1999 - May 2007)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.00	0.00	-1.14	0.25
Carry	0.21	0.03	6.34	0.00
Momentum	-0.02	0.04	-0.37	0.71
Value	0.07	0.03	2.67	0.01
Volatility	-0.05	0.07	-0.77	0.44

Table 4.8: Comprehensive Risk-adjustment regression for the *RiskMetrics* optimised FX carry portfolio (June 2007 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.25	0.21
Carry	-0.18	0.04	-4.69	0.00
Momentum	0.36	0.03	12.54	0.00
Value	0.07	0.04	1.91	0.06
Volatility	-0.13	0.08	-1.69	0.09

Table 4.9: Comprehensive Risk-adjustment regression for the *frontrunning* FX carry portfolio with lag 52 (January 1999 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.34	0.18
Carry	-0.13	0.07	-1.75	0.08
Momentum	0.05	0.04	1.24	0.22
Value	0.18	0.06	3.14	0.00
Volatility	-0.21	0.12	-1.79	0.07

Table 4.10: Comprehensive Risk-adjustment regression for the *frontrunning* FX carry portfolio with lag 52 (January 1999 - May 2007)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	0.44	0.66
Carry	-0.12	0.05	-2.59	0.01
Momentum	0.54	0.04	14.49	0.00
Value	-0.24	0.06	-3.96	0.00
Volatility	-0.07	0.09	-0.78	0.43

Table 4.11: Comprehensive Risk-adjustment regression for the *frontrunning* FX carry portfolio with lag 52 (June 2007 - March 2010)

Rolling-Window versus Fixed-Window VCV Estimation

A rolling window estimation of the VCV matrices could be better able to gauge potential structural changes within the data than an expanding window estimation since old and potentially irrelevant data is not included any more in the modelling. Therefore, we have also tested the performance of the two optimised FX carry portfolios based on VCV matrices which are estimated on a rolling fixed window length of 52 periods. In a first step, we estimated the *RiskMetrics* VCV matrix and the historical VCV matrix based on a rolling window with a constant

window length of 52 weeks. As with the fixed window estimation, our first sample starts on the 16th of January 1998.

The annualised return, standard deviation and Sharpe ratios for the expanding and rolling window portfolios are summarised below in Table 4.12. The sensitivity of the results with respect to a rolling or expanding estimation window vary based on the nature of the chosen VCV matrix estimator. The performance of the optimised portfolio based on the *RiskMetrics* VCV matrix is very insensitive with respect to the decision of whether to expand the window or roll it. The differences in performance concerning the annualised return and the annualised standard deviation are minimal and sharpe ratios are equal at 0.73. Conversely, we observe a somewhat higher impact on the backtesting results when the VCV matrix is estimated historically. The returns are slightly higher when the estimation window is rolled (2.87% versus 2.84%) and the standard deviation of returns is slightly lower when the window is rolled (4.49% versus 4.67%). Consequently the Sharpe ratio is slightly higher when the estimation window is rolled (0.64 versus 0.61).

These differences are due to the inherent differences on how the two methodologies weight historical information. Whereas each observed datapoint impacts the historical variance estimation with an equal weight, the *RiskMetrics* variance estimator will quickly decrease the relevance of older observations.

	Ann. Return	Ann. St.Deviation	Sharpe Ratio
Historical (Fixed Window)	0.0284	0.0467	0.61
Historical (Rolling Window)	0.0287	0.0449	0.64
RiskMetrics (Fixed Window)	0.0320	0.0440	0.73
RiskMetrics (Rolling Window)	0.0322	0.0440	0.73

Table 4.12: Annualised return, annualised standard deviation and Sharpe ratios of the optimised carry portfolios estimated with an expanding window and a rolling window of 52 periods.

4.6 Conclusion

As outlined in Section 4.1, a possible explanation for the enduring profitability of the carry trade is the limits to speculation hypothesis LSH, formulated by Lyons [2006] (see Section 4.1). The main statement of LSH is that market inefficiencies whose risk-adjusted returns do not surpass a specific threshold level, could persist

because of their limitation in attracting speculative capital. Since 5 out of 6 asset allocation algorithms (see Section 4.5) produced Sharpe ratios over the 0.4 threshold proposed by Sarno et al. [2006], we can discard the applicability of LSH to the FX carry trade. This finding confirms research results from Hochradl and Wagner [2010]. This result further proves the practical relevance of FX carry trade strategies for which we already found indications in literature (see Pojarliev and Levich [2008] and Section 3.3.2)

Also, we can confirm that diversification is beneficial to the trading performance of carry portfolios (see Burnside et al. [2006], Hochradl and Wagner [2010] and Vesilind [2006]). More specifically, we find that mean-variance optimisation has the potential of outperforming simple equally weighted asset allocation methodologies in the case of the FX carry trade. However, we show how the mean-variance asset allocation algorithms are sensitive to the choice of the variance-covariance matrix used for the optimisation. The *RiskMetrics* variance-covariance matrix produced a better Sharpe ratio than the historical variance-covariance matrix (Sharpe ratios of 0.73 against 0.61). We believe that more sophisticated VCV estimation methodologies, e.g. orthogonal GARCH (see Alexander [2001]), might further improve the backtesting results of FX carry portfolios. Nevertheless, even if on average the optimised FX carry portfolios produced better results than the simple scorecard-based FX carry portfolios, the higher transactions costs and the degrees of freedom associated with choosing an appropriate VCV matrix estimation methodology and its correspondent parameters, make well diversified, equally weighted carry portfolios seem the best choice in terms of tradeoff between diversification, performance and robustness. This intuition is confirmed by the regression results summarised in Table 4.5 which show that the optimised FX carry portfolios were not able to generate *carry-alpha* at a statistically significant level.

Furthermore, this paper examines two alternative approaches for generating currency portfolios based on the FX carry trade theme.

The first alternative approach consists in allocating the funds according to yields of a different maturity than the weekly rebalancing frequency. This approach illustrated that shorter term yields performed best when used for carry trading. Chinn and Meredith [2005] found that UIP is more likely to be violated for short maturity bonds than for long maturity bonds. Although our FX carry portfolios are rebalanced on a weekly basis instead of holding the currencies for

the whole maturity of the yields used for the ranking algorithm, the findings by Chinn and Meredith [2005] are reflected in the trading performance of our second set of FX carry portfolios.

The second alternative FX carry-related asset allocation approach consists in formulating and testing currency portfolios aimed at following the portfolio flows caused by FX carry traders in the market. We propose a simple methodology to implement such a trading strategy by ranking the currencies according to the momentum of their 2-Year yields and assuming equally weighted long (short) positions in the highest (lowest) ranked currencies. The assumption behind this approach is that positive yield changes in a currency tend to attract speculative carry capital, while negative yield changes would encourage carry traders to sell the respective currency short (see Section 3.3.2). We examined six different currency portfolios of this type, each based on a different lag length for the computation of yield momentum (see Section 4.3.3). Contrary to traditional FX carry portfolios, these yield-momentum based portfolios were not able to generate significant returns from the yield component while exhibiting positive returns from exchange rate movements.

We stress that this positive return from foreign exchange rate movements is inherent to the aggregated positions of the currency portfolios over time. Therefore, the predictability of single currencies is only given in certain situations when the criteria for inclusion in the *carry-flows* portfolios are met. Thus, our finding of the predictability of foreign exchange rates in the *carry-flows* portfolio context does not conflict with the finding by Meese and Rogoff [1983a] and Meese and Rogoff [1983b], who stated that the random walk model is the best model for explaining exchange rate movements.

The high transactions costs generated by the *carry-flows* portfolios, had a substantial impact on the final performance of the trading strategies. The best strategy in the third set of currency portfolios exhibited a Sharpe ratio of just 0.29. According to the LSH hypothesis (see Section 4.1) these relatively low risk-adjusted returns would not attract significant amounts of speculative capital. This would mean that the returns inherent to strategies following the portfolio-flows of FX carry traders will not disappear in the future.

Since the returns to the *carry-flows* portfolio strategies are linked to buy and sell pressure on currencies exercised by FX carry traders, we assume that there might be a correlation between the returns inherent to this type of strategy and

the amount of speculative capital tied to the FX carry trade. In a market environment where no one trades the FX carry trade, the profitable FX fluctuations inherent to the *carry-flows* portfolios should cease to exist.

From a portfolio management perspective, the *carry-flows* portfolios based on the longer lag lengths (i.e. $8-52$ periods) for computing the yield momentums (see Section 4.3.3) could serve as good diversification vehicles for FX carry portfolios, since they exhibit positive returns while delivering a negative loading on the FX carry factor in Equation 4.19 (see Table 4.5).

Chapter 5

Carry Trade Market Timing

5.1 Introduction

5.1.1 Market Timing

Following Taliaferro [2009], a fund times a market by adjusting its exposure to the market in advance of significant price action in that market. As an example Taliaferro [2009] referred to a fund that times the U.S. equities market by increasing its market exposure in advance of high aggregate market returns, and lowering its exposure in advance of low aggregate market returns.

If performed successfully, such market-timing has the potential to earn large profits. This has been shown, among others, by Shilling [1992] who found that during the period from 1946 to 1991 speculators could have increased their returns from 11.2% *per annum* to 19.0% *per annum* by exiting from the stock market during the 50 weakest months. Mistakes in market-timing decisions, such as exiting a profitable market too early may have severe implications as well. As Brunnermeier and Nagel [2004] showed, hedge funds that did not ride the technology bubble from 1998 to 2000 suffered large capital outflows, forcing some of them to liquidate.

Theoretical Feasibility of Market Timing The successful implementation of market-timing constitutes a particularly difficult task, and it is an open question whether real-money fund managers possess such market-timing ability (see Taliaferro [2009]). The theoretical discourse on the feasibility of market-timing in financial speculation is driven by two contrasting financial paradigms:

The Efficient Market Hypothesis EMH (see also Section 3.2.1) and *Behavioural Finance.*

Under the assumptions of the efficient market hypothesis, capital markets are efficient and investors rational. Prices reflect all information available to market participants at a specific point in time, and therefore investors should not be able to use currently available information to select profitable trades. Hence, according to the EMH, market-timing should not be feasible.

On the other hand, *Behavioural Finance* explicitly questions the assumptions set-up by the EMH, recognising that investors are irrational and are subject to specific behavioural biases such as overconfidence, information overload, herding, loss avoidance or anchoring (see Shleifer [2000]). By identifying and exploiting these behavioural biases, an investor has the possibility to generate excess returns from trading financial markets (see Heidorn and Siragusano [2004]). Thus, unlike the EMH, *Behavioural Finance* does not exclude the theoretical feasibility of market-timing.

Empirical Market Timing Literature An examination of the market-timing literature shows that different sets of market-timing-rules have been presented and tested with varying degrees of success. In this area of financial research, the U.S. equity market is the asset-class which received by far the most attention.

Starting with Sharpe [1975], many early studies were unable to find rules with the ability to time the market. This lead Clarke et al. [1989] to suggest that even people who think that it is possible to beat the market through stock selection seem to think that successful market-timing is impossible.

On the other hand, more recent studies present market-timing strategies and indicators which had the ability to outperform the market. For example, Shen [2002] presented simple market-timing strategies which are able to outperform a buy-and-hold strategy for the *S&P 500 Index.* The trading simulations are based on a dataset ranging from 1970 to 2000. Shen [2002] derived the successful trading rules from spreads between the earnings-to-price ratio of the *S&P 500 Index* and short term interest rates. He shows that a strategy which exits from the equity market when the earnings-to-price ratio to interest rates spread is under a predefined threshold was able to produce superior returns, even after including transactions costs. Brooks et al. [2005] expanded on the results presented by Shen

[2002] by focusing on a very long dataset of the *S&P 500 Index* and a wider range of market-timing indicators and rules to derive the market exposure in the *S&P 500 Index*. Brooks et al. [2005] found that all but one of the suggested approaches were able to beat the buy-and-hold benchmark in risk-adjusted terms. The best strategy is based on the spread between the earnings-to-price ratio and short term treasury yields, confirming the results of Shen [2002].

A further study on market-timing strategies is the paper by Faber [2009]. Faber [2009] presented a quantitative market-timing framework based on simple moving averages. He applied the same methodology for market-timing on the United States equity market since 1900, and on other diverse and publicly traded asset class indices including the Morgan Stanley Capital International EAFE Index, the Goldman Sachs Commodity Index, the National Association of Real Estate Investment Trusts Index and United States government 10-year Treasury bonds, since 1973. The market-timing model was able to improve risk-adjusted returns on most tested markets. Utilising a monthly system since 1973, an investor would have been able to avoid being invested during many of the protracted bear markets in various asset classes. Avoiding these large losses would have resulted in equity-like returns with bond-like volatility and drawdown.

Market Timing in Real-World Investing Brooks et al. [2005] posed the question whether real-money portfolio managers are applying market-timing techniques for the allocation of their assets. He provides qualitative evidence that fund managers make significant changes to the composition of their portfolios when they believe that assets they hold are overvalued and could fall in value.

The yearly *Quantitative Analysis of Investor Behaviour* study by Dalbar Inc. Dalbar [2010] provided some quantitative evidence concerning the ability of equity funds to time the market. The study found, that while the *S&P 500 Index* has returned 8.20% *per annum* over a 20 year period ending in December 2009, the average equity fund investor has earned only 3.17% *per annum*. These results suggest that the market-timing ability of fund managers is limited and that an investor should invest in a broad market index instead of trying to outperform the market through market-timing techniques. However, the Dalbar study is based on a wide range of institutional investors and thus it cannot exclude that individual portfolio managers might possess market-timing ability.

A further investigation on fund managers' ability to time the market has been performed by Bollen and Busse [2001]. He found increased evidence for market-

timing ability of fund managers when analysing the dataset on a daily frequency instead of a monthly frequency and concludes that fund managers might possess a better market-timing ability than previously documented in literature.

More recently, Chen and Liang [2006] analysed a data set consisting of the returns of 221 mutual funds which adopt market-timing strategies. In his investigations on the market-timing ability of these funds, he found statistically significant evidence for market-timing ability at both the aggregate and individual levels. The results also indicate a higher market-timing ability by the funds during periods of falling equity prices and high volatility.

Evidence for market-timing ability by FX hedge-funds has been found by Pojarliev and Levich [2008], a more detailed discussion of which can be found in the subsequent Section 5.1.2.

5.1.2 Foreign Exchange Investment-Style Timing

In Section 3.1 we discussed new benchmarks for currency managers based on the FX investment-styles carry, momentum, volatility and valuation. These benchmarks can be tracked at low cost through e.g. ETF's (see Section 3.1.2). According to Pojarliev and Levich [2008], such a market environment creates the need for innovative *alpha* strategies that produce returns which can not be explained by popular investment-style proxies.

Pojarliev and Levich [2008] showed that professional currency managers have the ability to generate 'genuine' *alpha*, i.e. returns not explicable by typical FX investment-styles. Further, he investigates whether the *alpha* generated by these FX funds comes from successful market-timing activity in any of the major FX investment-styles. The results indicate that, out of a data sample of 34 FX hedge funds from 2001 to 2006, about half of the examined funds possessed statistically significant market-timing ability in one or more of the four major FX investment-styles.

More specifically

- 3 out of 34 funds (8.82%) were able to time the *carry* investment-style,

- 7 out of 34 funds (20.56%) were able to time the *trend* investment-style,

- 3 out of 34 funds (8.82%) were able to time the *valuation* investment-style,

- 6 out of 34 funds (17.65%) were able to time the *volatility* investment-style.

Pojarliev and Levich [2008] concluded that some FX hedge funds possess market-timing ability. This result raises the question of how these funds actually perform the investment-style timing. Empirical literature on market-timing strategies for FX investment-styles is scarce. The issue has been addressed mainly by Dunis et.al. in a set of research papers (see Dunis and Miao [2005], Miao and Dunis [2006] and Dunis and Miao [2007]).

Dunis and Miao [2005] studied the returns inherent to technical trading strategies on a set of currency pairs. The trading strategies are based on the MACD indicator, a popular indicator in technical analysis. Dunis and Miao [2005] found that the returns of technical trading strategies for individual currency pairs are related to the volatility regime of the currency pair. More specifically, the technical strategies exhibited higher returns in periods of relatively low volatility and lower, often negative, returns during periods of high market volatility. [1]

In a subsequent paper, Miao and Dunis [2006] applied volatility-based trading filters on the *AFX Index*[2]. In addition to the *RiskMetrics* methodology, some alternative procedures for the estimation of the FX volatility are used. The two alternative volatility forecast models used in Miao and Dunis [2006] are the GARCH model and a stochastic volatility model with Markov switching. Similarly to Dunis and Miao [2005], the returns inherent to the FX trend investment-style are negatively related to FX market volatility. Trading filters based on FX volatility proxies improve the returns to the *AFX Index* in risk-adjusted terms. Further, the results indicate that the alternative volatility models fail to improve the performance of the *RiskMetrics* volatility model, when used as switching filters for trading the FX momentum investment-style.

Dunis and Miao [2007] examined the performance of returns to the FX carry trade during different regimes of (*RiskMetrics*) FX volatility. Dunis and Miao [2007] found that, similarly to the case of momentum strategies, FX carry trade returns deteriorate during periods of high FX market volatility. Subsequently, Dunis and Miao [2007] applied the market-timing methodology proposed in Miao and Dunis [2006] to the FX carry trade. The results indicate that the addition of volatility filters for FX carry trading produces better risk-adjusted returns than trading a long-only carry portfolio: While the long-only carry strategy produced

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[1]Dunis and Miao [2005] calculated the FX volatility proxy via the *RiskMetrics* methodology (see Section 4.4.3).

[2]The *AFX Index* constitutes a proxy for the momentum investment-style in the FX market (see Section 3.1.2).

a sharpe ratio of 1.04 from January 1999 to March 2005, the market-timed carry strategies produced sharpe ratios of 1.37 in the case of the long-neutral filter, and 1.43 in the case of the long-short filter.

5.1.3 Market Timing Indicators for FX Carry Portfolios

Market-timing rules usually build on empirical findings of the ability of certain indicators to predict future market performance. The literature has identified many useful indicators for timing the equities markets. Examples for these indicators are the earnings-to-price ratio, the dividend yield, the dividend-payout ratio, the maturity spread and the credit spread and the gilt-equity yield ratio (see Neuhierl and Schlusche [2009]).

Since our purpose is to study the performance of market-timing the FX carry trade, we would like to utilise market-timing indicators which are more specific to the FX markets and the FX carry trade. Apart from Dunis and Miao [2005], Miao and Dunis [2006] and Dunis and Miao [2007], which proposed the use of *RiskMetrics* FX market volatility as a timing-indicator for FX investment strategies, we are not aware of any published academic research on the market-timing of FX trading styles.

Nevertheless, we are able to identify some data categories which could provide useful market-timing indicators for the FX carry trade. The data categories from which we will choose the indicators used for the empirical research in Section 5.5 are:

- Volatility

- Liquidity

- FX Yield Differentials

- Aggregate Risk-Aversion Indicators

In the following, we will briefly discuss these indicator categories. In Section 5.3 we will choose and present specific market-timing indicators from these categories.

Volatility We expect periods of high global volatility to coincide with weak FX carry trade performances and *vice versa*. The reason for this is that periods of high market volatility often occur during periods of financial turmoil (see Whaley

[2000]). Such market environments are negative for the FX carry trade (see Section 3.3.3).

We find evidence in literature for volatility as a successful indicator for FX carry trade returns. Carins and McCauley [2007] found indications for a relationship between increases in the VIX[3] and depreciation of the USD against the JPY, a major carry trading currency pair during the period under examination. Menkhoff et al. [2009] found a statistically significant negative relationship between the returns of high yielding currencies and global volatility levels. Similarly, Vistesen [2009] found that low yielding currencies (the JPY and CHF) can be successfully modelled as a negative function of equity returns and a positive function of volatility in the market. carry trade strategies would suffer from these scenarios. Furthermore, as discussed in Section 5.1.2, Miao and Dunis [2006] and Dunis and Miao [2007] have shown that proxies for FX market volatility can serve as successful market-timing filters for the trend investment-style and the carry investment-style.

Liquidity　We expect FX carry trade performance to deteriorate during periods of low market liquidity. As in the case of high aggregate market volatility, periods of low liquidity tend to coincide with financial market turmoil and investor uncertainty (see Allen and Carletti [2008]), which are bad market conditions for carry trading strategies.

This rationale is confirmed by Menkhoff et al. [2009], who showed that liquidity risk matters for excess returns to the FX carry trade, although to a lesser extent than volatility.

FX Yield Differentials　The motivation behind using yield differentials as timing factors for FX carry portfolios is based upon the observation that foreign exchange rate portfolio flows are statistically significantly related to measures of carry trade attractiveness like e.g. the yield differentials on currency positions (see Galati et al. [2007b] or 3.3.2). This observation means that currency investors would tend to hold larger amounts of currency, as the possibility to generate a pickup in yields rises. Thus, using yield differentials as a timing factor for FX carry trades can constitute a very simplistic model of the observed behavior of FX portfolio managers which drives foreign exchange rate transactions.

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[3]See Section 5.3.2.

Market timing FX carry portfolios based on the level of the earned yield differentials aims at *frontrunning* the empirically observed behavior of FX speculators, thus opening up the opportunity for capitalising on the price fluctuations induced by the buying and selling pressures of the FX maket participants. To our knowledge, no research on the profitability of FX carry trade timing with this indicator has been performed.

Aggregate Risk-Aversion Indicators   Several authors have expressed the idea that constructing indices that track the general risk-aversion in the markets could be useful for timing FX carry trades (see Rosenberg [2003] or Vesilind [2006]). Such approaches are also popular in quantitative research publications in the financial industry, which markets them as profitable market-timing indicators for FX strategies. For a more extensive discussion of aggregated risk aversion indicators used in the financial industry we refer to Bundesbank [2005].

Despite the interest shown, we stress that up to this point academia has provided no evidence for the profitability of rules based on these indicators. Vesilind [2006] mentioned that his attempts to construct and use an aggregate risk appetite index for timing the FX carry trade, did not improve the cumulative performance of the strategy. Vesilind [2006] failed to provide the methodology and empirical results behind his conclusion.

5.2   Contributions

In the remainder of this chapter we continue our empirical investigation on quantitative methodologies for trading FX carry portfolios. The central research question which we pose here asks whether market-timing signals based on a variety of risk factors (see Section 5.1.3) are suitable for actively trading FX carry portfolios. The market-timing signals which determine when to take a long, neutral or short position in the FX carry trade are computed using a simple signal generation methodology (see Section 5.4.1) in order to keep the results transparent and replicable. To our knowledge, except in Dunis and Miao [2007], such a treatment of the FX carry investment-style as an underlying financial instrument in its own right has not been performed before. Thus, this chapter contributes to the limited body of literature on market-timing strategies for FX investment-styles (see Section 5.1.2).

As Pojarliev and Levich [2008] showed, active trading of FX investment-styles

is being performed by a good number of FX hedge funds. This is is not surprising, since the possibility of low-cost replication of FX hedge fund returns makes the service of professional (and expensive) FX managers seem useless, if they do not deliver currency *alpha* as understood by Pojarliev and Levich [2008]. The research performed in the following sections therefore contributes to the research on modern FX hedge fund strategies which still have to be uncovered.

Furthermore, our analysis may deliver new insights into the mechanics of the forward rate bias, which is directly linked to FX carry trade returns. Recent literature on the drivers of carry trade profits studies the relationship between risk factors and carry trade returns by fitting linear regressions and searching for statistically significant coefficients (see Section 3.3.4). In contrast to that line of research, we choose to assess the relevance of the risk factors for FX carry trade returns by evaluating the financial performance metrics of market-timed FX carry portfolios.

The logic behind the construction of the market timed trading rule is analogeous to the logic behind the *perceptron* which constitutes the smalles unit of an artificial neural network (see e.g. Zimmermann and Rehkugler [1994] and Grimm [1997]). Like the market timing filter, a *perceptron* receives a set of inputs and outputs a transformed version of these inputs. Mostly the output of a perceptron consists of binary data which is calculated depending on whether the input surpasses a given threshold level or not. *Perceptrons* represent the most basic version of artificial neural networks, whose strength lies in their capability to approximate highly dimensional and nonlinear functions. Thus, a successful (i.e. profit-enhancing) application of a market-timing rule would signal the presence of a nonlinear relationship between the specific risk factor and the strength of the forward rate bias. We note that other approaches which are able to model and capture nonlinear dynamics have been presented in financial research. Examples for these models are Feedforward and Recurrent Neural Networks, Markov Switching models, Threshold Autoregression models and Smooth Transition Autoregression models, just to name a few. We refer to Mills and Markellos [2008] for a survey on nonlinear time series analysis in financial economics.

In addition to the financial performance evaluation metrics, we will test the presented trading-strategies for *carry-alpha* generation and market-timing ability (see Section 5.4.2).

5.3 Data

In order to test the performance of market-timed FX carry portfolios we require a set of data series specific to the *Benchmark FX Carry Portfolio*, as well as a set of risk-indicators.

Our data set starts on the 01.01.1999 and ends on the 05.03.2010. Since we lose 50 observations for the calculation of the market-timing signals (see Section 5.4.1), the backtesting period for the portfolios in this chapter starts on the 10.12.1999 and ends on the 05.03.2010 (534 weekly observations). In the following sections we describe the relevant datasets for the empirical analyses conducted in this chapter.

5.3.1 The Benchmark FX Carry Portfolio

The starting point for the analysis of our market-timing algorithms is the *Benchmark FX Carry Portfolio*. Details concerning the raw data sources, the methodology and the performance of the *Benchmark FX Carry Portfolio* are outlined in Appendix A.

The portfolio yield differentials inherent to the *Benchmark FX Carry Portfolio* (see Section A.5), as well as the *RiskMetrics* conditional volatility estimates of this portfolio (see Section A.5) will serve as inputs to the market-timing methodology described in Section 5.4.1.

5.3.2 Carry Timing Indicators

In the following paragraphs, we provide an overview of the financial time series which will be used to construct the market-timing signals for actively trading the FX carry trade. A visual representation of these time series is given in the left-hand-side of Figure 5.1.

VIX (CBOE S&P 500 Volatility Index) The VIX is an index of the expected return volatility of the S&P 500 Index over the next 30 days (see Whaley [2008]). The values of the VIX are calculated in real-time by the *Chicago Board Options Exchange*. The quoting methodology is analogous to the pricing of variance swaps (see CBOE [2009]), using prices from different traded options on the S&P 500 Index to determine the expected return volatility.

The VIX is sometimes called 'the fear gauge' by the financial industry, since it is often used to represent equity market volatility as well as risk aversion (see Lustig et al. [2008] and Whaley [2000]). As discussed in Section 5.1.3, we would expect high values of the VIX to signal negative periods for the FX carry trade.

CarryVola (Benchmark FX Carry Portfolio *RiskMetrics* Volatility) We compute the *RiskMetrics* volatility on the *Benchmark FX Carry Portfolio* (see Section A.5) as a proxy for FX market volatility specific to the FX carry trade. As shown by Dunis and Miao [2007], we expect high values of FX market volatility to coincide with periods of negative carry performance.

USSP2 (2-Year U.S. Swap Spread) The *2-Year U.S. Swap Spread* denotes the difference between the 2-year swap rate and the yield on a government bond with 2-year maturity (see Cortes).

Possible interpretations of swap spread dynamics range from an indicator of systemic risk in the banking sector to an indicator for credit and/or liquidity risk (see Kobor et al. [2005]). A study by Huang et al. [2002] agreed with the prevailing view among swap traders that swap spreads are mainly an indicator of market liquidity risk. Therefore, as discussed in Section 5.1.3, we would expect high values of the *2-Year U.S. Swap Spread* to signal negative periods for the FX Carrry Trade.

TEDSP (Ted Spread) The *Ted Spread* is is defined as the interest rate difference between 3-month Libor and 3-month T-bill rates (see Menkhoff et al. [2009]).

Differences between these rates reflect, among other things, the willingness of banks to provide funding in the interbank market: When the *TED Spread* increases, that is a sign that lenders believe the risk of default on interbank loans is increasing. Interbank lenders therefore demand a higher rate of interest, or accept lower returns on safe investments such as T-bills. When the risk of bank defaults is considered to be decreasing, the TED spread decreases. The TED Spread can be interpreted as a measure for illiquidity in global money markets (see Brunnermeier et al. [2008] and Menkhoff et al. [2009]). Again, as discussed in Section 5.1.3, as with the swap spread we would therefore expect high values of the TED Spread to signal negative periods for the carry trade.

CarryYield (Benchmark FX Carry Portfolio Yield Differential) The overall yield differential of the FX positions in the *Benchmark FX Carry Portfolio* (see Section A.5) is used to proxy the attractiveness of setting up diversified carry trades, as far as the pure carry component is concerned. We expect high interest rate differentials to be beneficial to carry trading strategies, since they allow for larger FX drawdowns before generating an overall loss to the FX carry Portfolio.[4]

5.4 Methodology

In the following sections the methodology for the derivation of market-timing rules and statistical tests for market-timing ability are presented.

5.4.1 Market-Timing Rules

We employ and compare 3 different sets of market-timing rules:

- **Simple** An approach based on the methodologies proposed by Brooks et al. [2005] and Dunis and Miao [2007], utilising the risk indicators described above.

- **Average** An approach based on the average market-timing signal derived from the first approach.

- **Majority** An approach based on the majority vote market-timing signal derived from the first approach.

In the following paragraphs these methodologies for market-timing rule creation are presented in more detail.

Simple The simple market-timing algorithm, is derived from the methodologies proposed by Brooks et al. [2005] and Dunis and Miao [2007].

Brooks et al. [2005] exited the market, when the relevant risk indicator value is over its historical 90th percentile. Instead of calculating the value of the 90th percentile in each week, we have chosen to calculate the p-values ϕ^I of the specific

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[4]Note that in the subsequent analyses we invert the value of the *CarryYield* indicator to be congruent with the other indicators (s.t. high values have a negative influence on FX carry trades).

risk indicator I. The p-value indicates the percentage of values which historically have been smaller than the actual value of a specific time series. As an example, a p-value of 0.65, indicates that on that particular week the specific indicator is larger than 65% of its historical realisations. The rolling p-values for all risk indicators used in this chapter are depicted in Figure 5.1.

Analogous to Dunis and Miao [2007] we test 2 different filter rule settings, i.e. long-neutral and long-short. In the long-neutral setting, the possible market positions for the FX carry trade Strategy are either long or neutral. In the long-short setting, long as well as short positions in the FX carry trade can be assumed. Computationally we specify [$long/neutral/short$] positions with the identifiers [$1/0/-1$].

In order to calculate a simple market-timing signal, the following parameters have to be set once:

- Select the relevant risk indicator I (e.g., $I = VIX$)

- Set the p-value ϕ^I threshold level L (e.g., $L = 0.7$)

- Set the filter-rule setting (long-neutral or long-short)

Subsequently, the following calculations have to be performed <u>each week</u> ($t = 50, ..., T$) on a rolling basis, to ensure the real-time character of the trading simulations. Note that the first data window contains 50 observations. Each week the dataset on which the p-value calculations are based will expand to include every observation starting from the 01.01.1999 and ending on the respective date in the rolling procedure.

1. Calculate the actual p-value p_t^I

2. Calculate the actual market position MP_t^I:

$$
MP_t^I = \begin{cases} 1, & \text{if } \phi_t^I <= L \\ 0, & \text{if } \phi_t^I > L \text{ and long-neutral setting} \\ -1, & \text{if } \phi_t^I > L \text{ and long-short setting} \end{cases} \tag{5.1}
$$

Throughout the calculations, we arbitrarily set the threshold L to 0.7. A test of multiple threshold values has been intentionally omitted, in order to avoid the problem of data-mining.

Average The *average* market-timing signal consists of a weighted average of all computed *simple* market-timing signals. The steps involved in the calculation of the *average* market-timing signal in a specific week t are:

1. Calculate the simple market-timing signals for all available risk indicators.

2. Compute the average of all market-timing signals.

Also the *average* market-timing signal will be tested for the long-neutral and long-short strategy settings.

Majority Similar to the *average* market-timing signal, the *majority* market-timing signal considers all simple market-timing signals. Here, the market-timing signal which is exhibited by the majority of the simple market-timing, will be chosen. The steps involved in the calculation of the *majority* market-timing signal in a specific week t are:

1. Calculate the simple market-timing signals for all available risk indicators.

2. Select the market-timing signal which is most prevalent amongst all simple market-timing rules.

Figure 5.1 depicts the raw risk indicators (left-hand-side) and the corresponding rolling p-values ϕ with the chosen threshold level L (right-hand-side). Figure 5.2 depicts the market positions MP for all market-timing rules in the long-neutral setting (left-hand-side) and the long-short setting (right-hand-side).

5.4.2 Statistical Test for Market-Timing Ability

After simulating the performance of the market-timed FX carry portfolios, we want to test whether the market-timing rules exhibit statistically significant market-timing ability.

We follow the approach proposed by Treynor and Mazuy [1966], who were among the first to propose a dynamic measure of active management. To detect market-timing skills, Treynor and Mazuy [1966] augmented the linear framework presented in Section 4.4.4 with a quadratic term. Thus, in order to test for the ability of the market timing rules to generate abnormal returns, we perfrom regressions of the following form:
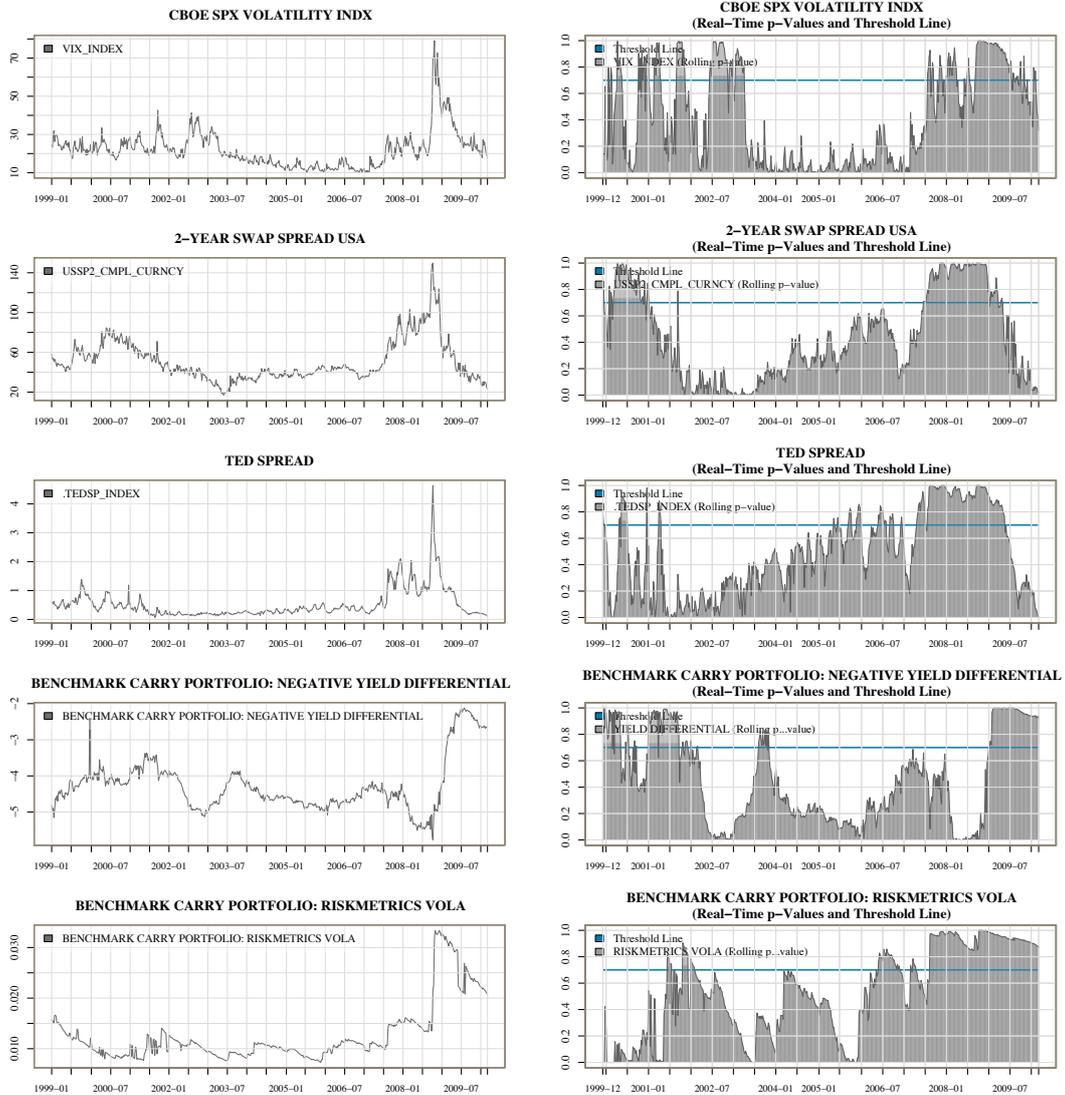
Figure 5.1: Risk Factors (left-hand-side) and Market-Timing-Signal Construction
Methodology (right-hand-side).
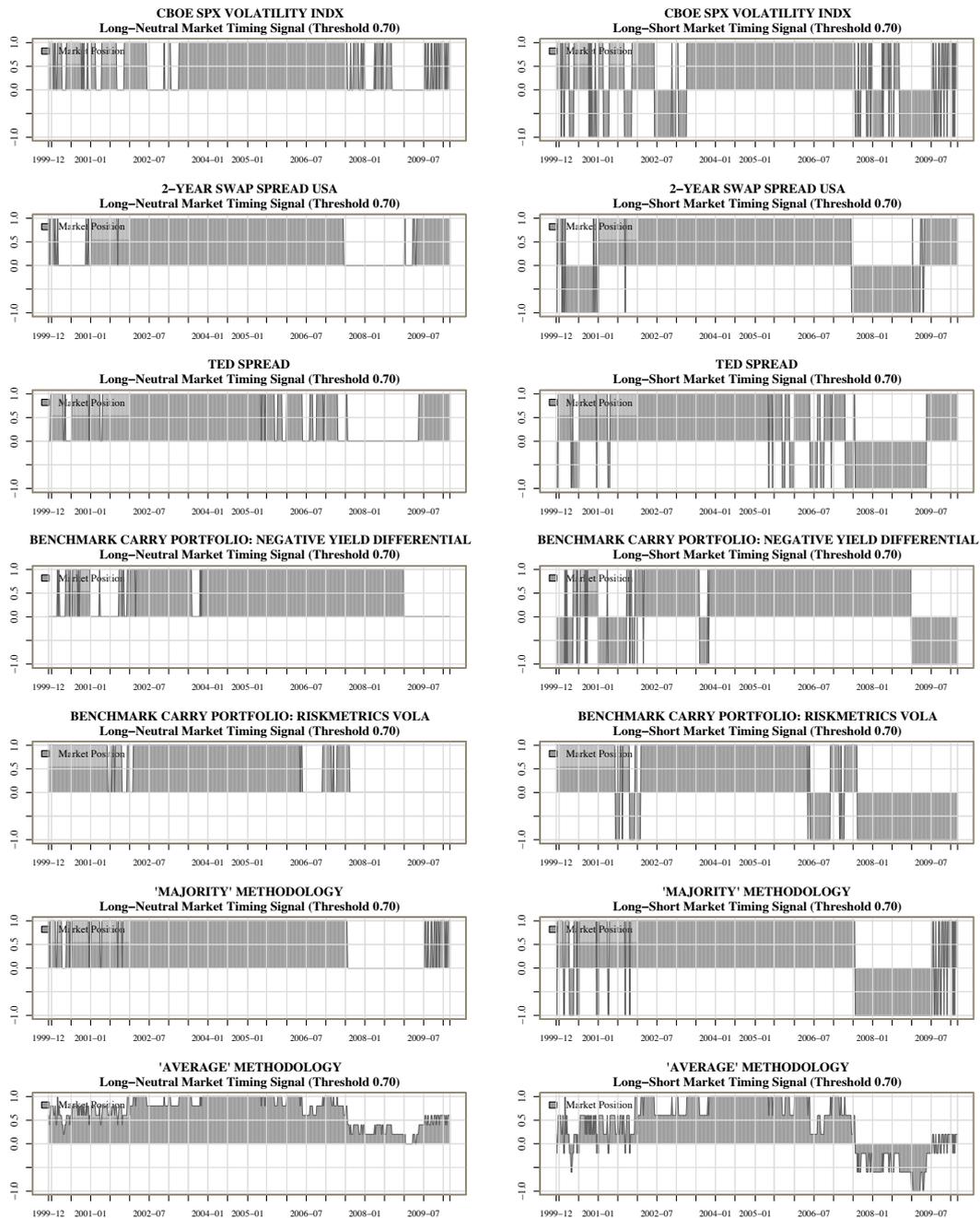
Figure 5.2: Long-Neutral (left-hand-side) and Long-Short (right-hand-side) Market-Timing Signals.

$$R_t = \alpha + \beta F_t + \gamma F_t^2 + \epsilon_t \tag{5.2}$$

where R_t is the excess return generated by the market-timed *Benchmark FX Carry Portfolio* in week t, F_t is the excess return generated by *Benchmark FX Carry Portfolio* in week t, F_t^2 the squared excess return generated by *Benchmark FX Carry Portfolio* in week t, α (the intercept) is a measure of active trading rule skill, β is the coefficient for the *Benchmark FX Carry Portfolio* factor, γ is the coefficient for the squared *Benchmark FX Carry Portfolio* factor and ϵ is a random error term.

A statistically significant positive γ coefficient would signal market-timing ability of the specific market-timing rule.

We note that a good number of alternative approaches to test for market timing ability have been presented in literature.[5] Our choice for the particular approach in Equation 5.2 follows the methodology of Pojarliev and Levich [2008], whose contribution on active FX management performance attribution is of central importance to our research on the FX carry trade.

5.5 Empirical Results

5.5.1 Discussion of the FX Carry Portfolio Market-Timing Performances

In this chapter we tested the performance of trading FX carry portfolios with market-timing signals based on risk indicators. We utilised different risk indicators and analysed long-neutral and long-short trading filters for the FX carry trade. We will now interpret the effects of market-timing FX carry portfolios, by examining the results in Table 5.1, Table 5.2, Table 5.3 and Figure 5.3.

Table 5.1 summarises performance metrics and return attribution measures for the market-timed FX carry portfolios. The first column of Table 5.1 describes the allowed positions which are used for the market-timing experiments. The allowed positions are long-neutral and long-short. The second column ('*Indicator*') of Table 5.1 describes the chosen risk indicator for the computation of the market-timing signal. In the third and fourth columns the annualised arithmetic return

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[5]See e.g. the Henriksson/Merton test (see Merton [1981b] and Merton [1981a]), the Connor/Korajczyk model (see Connor and Korajczyk [1991]) and the Bhattacharya/Pfleiderer model (see Bhattacharya and Pfleiderer [1983]).

r^a and the Sharpe ratio SR are listed for each currency portfolio. The last three columns of Table 5.1 allow us to identify the source of the strategy total returns listed in the r^a-column: r^a_{FX} represents the annualised arithmetic returns generated from FX movements, r^a_{YD} the annualised arithmetic return generated from yield pickup and r^a_{TC} represent the annualised transactions costs in percent. Figure 5.3 depicts the cumulative performance of the market-timed FX carry portfolios. Table 5.2 summarises the regression results of the factor model testing for the ability of the market-timing signals to generate *carry-alpha*. Table 5.3 summarises the regression tests for market-timing ability of the market-timing signals.

Timing	Indicator	r^a	SR	r^a_{FX}	r^a_{YD}	r^a_{TC}
Long-Only	-	0.0639	0.64	0.0242	0.0425	-0.0028
Long-Neutral	VIX	0.0433	0.69	0.0204	0.0301	-0.0071
Long-Neutral	USSP2	0.0780	1.16	0.0510	0.0308	-0.0038
Long-Neutral	TEDSP	0.0603	0.97	0.0351	0.0298	-0.0045
Long-Neutral	YDDIFF	0.0321	0.38	0.0025	0.0337	-0.0041
Long-Neutral	RISKM	0.0469	0.81	0.0220	0.0286	-0.0037
Long-Neutral	MAJVOTE	0.0619	0.99	0.0349	0.0324	-0.0053
Long-Neutral	AVGSIGNAL	0.0512	0.91	0.0251	0.0306	-0.0044
Long-Short	VIX	0.0204	0.20	0.0166	0.0170	-0.0132
Long-Short	USSP2	0.0900	0.91	0.0779	0.0186	-0.0063
Long-Short	TEDSP	0.0547	0.55	0.0460	0.0165	-0.0078
Long-Short	YDDIFF	-0.0032	-0.03	-0.0192	0.0243	-0.0083
Long-Short	RISKM	0.0276	0.28	0.0199	0.0140	-0.0062
Long-Short	MAJVOTE	0.0579	0.58	0.0456	0.0217	-0.0093
Long-Short	AVGSIGNAL	0.0378	0.57	0.0260	0.0184	-0.0066

Table 5.1: Performance Metrics of the Market-Timed FX Carry Portfolios (r^a: Annualised Arithmetic Return, SR: Sharpe Ratio, r^a_{FX}: Annualised Return from FX movements, r^a_{YD}: Annualised Return from Yield Differentials, r^a_{TC}: Annualised Return from Transactions Costs)

Market-Timed FX Carry Portfolios (Long-Neutral Setting) Analysing the performance metrics in Table 5.1 we see that the long-neutral market-timed FX carry portfolios outperformed the *Benchmark FX Carry Portfolio* in 6 out of 7 cases: The Sharpe Ratios of the 6 top-performing market-timing signals range between 0.69 and 1.16, while the long-only *Benchmark FX Carry Portfolio* generated a Sharpe Ratio of 0.64 during the relevant data period (see Section 5.3). The best simple market-timing signals are based on the time series which proxy liquidity risk. Timing the carry trade with these signals generated high absolute Sharpe ratios of 1.16 in the case of the 2-Year U.S. Swap Spread (USSP2) and 0.97 in the case of Ted Spread (TEDSP) as a liquidity proxy. The simple volatility-based timing signals also performed well, generating a Sharpe ratio of 0.81 in the
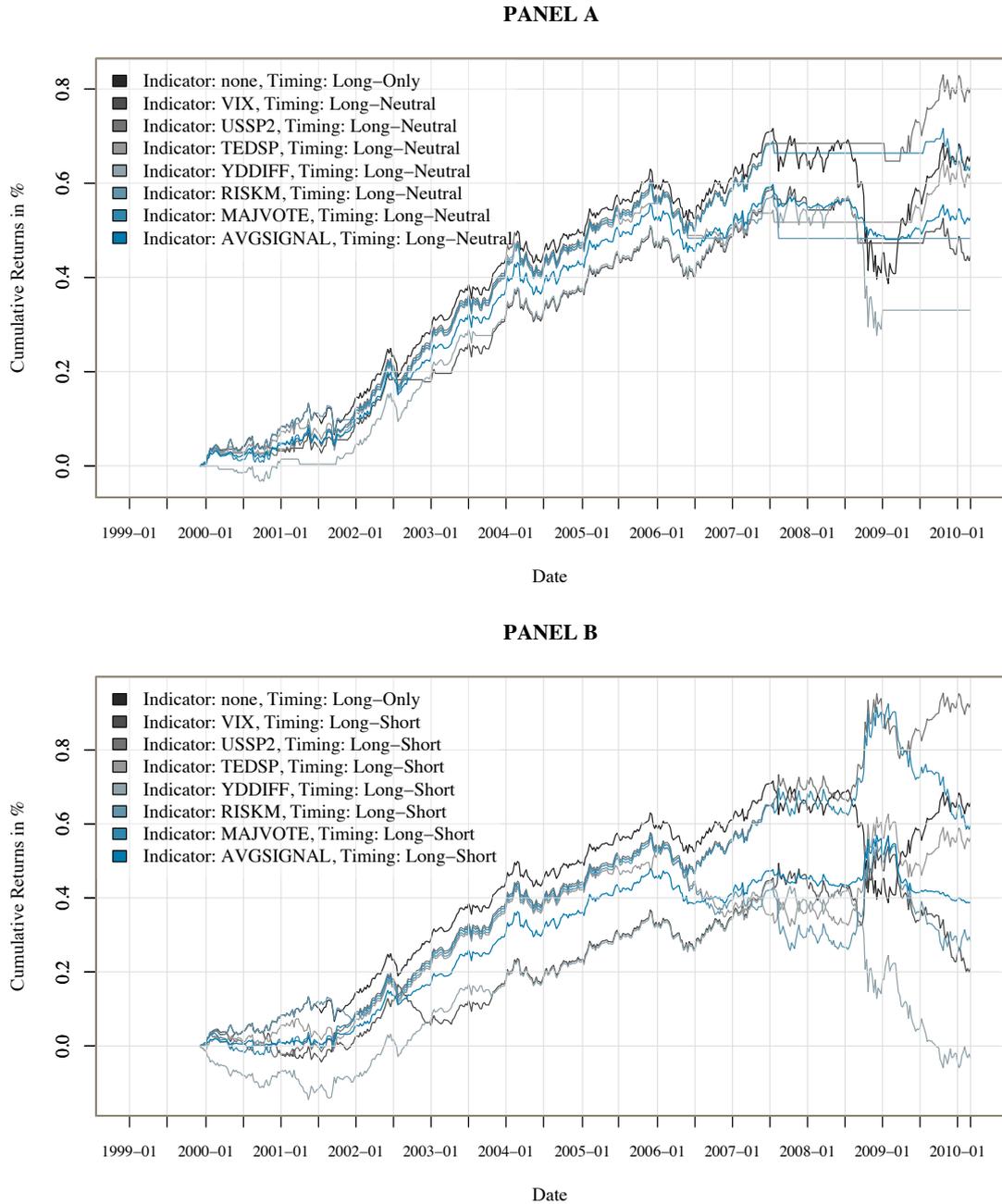
PANEL A

PANEL B

Figure 5.3: Cumulative Returns for Long-Neutral (PANEL A) and Long-Short (PANEL B) Market-Timed FX Carry Portfolios.

Timing	Indicator	α	$Pr(> \|t_\alpha\|)$	β	$Pr(> \|t_\beta\|)$
Long-Neutral	VIX	0.0003	0.24	0.39	0.00
Long-Neutral	USSP2	0.0009	0.00	0.46	0.00
Long-Neutral	TEDSP	0.0007	0.02	0.39	0.00
Long-Neutral	YDDIFF	-0.0003	0.27	0.74	0.00
Long-Neutral	RISKM	0.0005	0.09	0.34	0.00
Long-Neutral	MAJVOTE	0.0007	0.02	0.39	0.00
Long-Neutral	AVGSIGNAL	0.0004	0.03	0.46	0.00
Long-Short	VIX	0.0007	0.27	-0.21	0.00
Long-Short	USSP2	0.0018	0.00	-0.08	0.05
Long-Short	TEDSP	0.0013	0.02	-0.23	0.00
Long-Short	YDDIFF	-0.0006	0.22	0.48	0.00
Long-Short	RISKM	0.0009	0.11	-0.32	0.00
Long-Short	MAJVOTE	0.0014	0.02	-0.22	0.00
Long-Short	AVGSIGNAL	0.0008	0.04	-0.08	0.01

Table 5.2: Regression Results for the Factor Model $R_t = \alpha + \beta F_t + \epsilon_t$ (F_t = Benchmark FX Carry Portfolio Returns, R_t = Market Timed Carry Portfolio Returns).

Timing	Indicator	α	$Pr(> \|t_\alpha\|)$	β	$Pr(> \|t_\beta\|)$	γ	$Pr(> \|t_\gamma\|)$
Long-Neutral	VIX	-0.0000	0.72	0.43	0.00	2.18	0.00
Long-Neutral	USSP2	0.0000	0.53	0.52	0.00	3.53	0.00
Long-Neutral	TEDSP	0.0000	0.63	0.43	0.00	2.55	0.00
Long-Neutral	YDDIFF	0.0000	0.20	0.69	0.00	-3.03	0.00
Long-Neutral	RISKM	0.0000	0.52	0.36	0.00	1.38	0.00
Long-Neutral	MAJVOTE	0.0000	0.59	0.43	0.00	2.59	0.00
Long-Neutral	AVGSIGNAL	0.0000	0.43	0.48	0.00	1.22	0.00
Long-Short	VIX	-0.0000	0.68	-0.14	0.00	4.32	0.00
Long-Short	USSP2	0.0000	0.57	0.03	0.48	7.03	0.00
Long-Short	TEDSP	0.0000	0.67	-0.14	0.00	5.07	0.00
Long-Short	YDDIFF	0.0000	0.24	0.38	0.00	-6.05	0.00
Long-Short	RISKM	0.0000	0.56	-0.28	0.00	2.73	0.01
Long-Short	MAJVOTE	0.0000	0.62	-0.14	0.00	5.14	0.00
Long-Short	AVGSIGNAL	0.0000	0.45	-0.04	0.17	2.41	0.00

Table 5.3: Regression Results for the Factor Model $R_t = \alpha + \beta F_t + \gamma F_t^2 + \epsilon_t$ (F_t = Benchmark FX Carry Portfolio Returns, R_t = Market Timed Carry Portfolio Returns).

case of the RiskMetrics carry portfolio Volatility based timing signal (RISKM), and 0.69 in the case of the S&P 500 Volatility Index based timing signal (VIX). The market-timing signal that exhibited the worst backtesting performance was based on the Yield Differentials (or the *carry*) time series inherent to the *Benchmark FX Carry Portfolio*s (YDDIFF). This strategy generated a relatively low Sharpe ratio of 0.38 and was the only one that failed to improve the long-only carry strategy in the long-neutral setting. The two aggregated market-timing signals generated performances which are comparable to the performances achieved by the best simple market-timing signals: The Sharpe ratio of the average timing signal (AVGSIGNAL) was 0.91 and the Sharpe ratio of the majority-vote timing signal (MAJVOTE) was 0.99.

The return attribution measures in the right-hand-side of Table 5.1 show that all long-neutral timed carry portfolios generated good returns from the yield component. These returns range between 2.98% *per annum* and 3.37% *per annum* during the relevant data period. Since in this setting we never assume short positions in the carry strategy, the return from yield has to be positive by construction. A feature shared by the top three performing long-neutral market-timed FX carry portfolios is that they were able to generate higher returns from FX fluctuations than from the yield pickup. The 2-Year U.S. Swap Spread (USSP2) based timing signal generated a return of a 5.10% *per annum* from currency movements against a return of 3.08% *per annum* from yield differentials, the Ted Spread (TEDSP) based timing signal generated return of 3.51% *per annum* from currency movements and a return of 2.98% *per annum* from yield differentials, and the Majority-Vote (MAJVOTE) timing signal generated a return of 3.49% *per annum* from currency movements and a return of 3.24% *per annum* from yield differentials. Thus, the strength of the most profitable long-neutral market-timing strategies is their ability to selectively assume positions in the carry trade when the risk of incurring drawdowns from currency fluctuations is relatively small. On the other hand, the worst performing long-neutral timed carry portfolio generated practically no return from fluctuations in exchange rates: While generating the highest return from interest rate differentials amongst the long-neutral timed carry portfolios (3.37% *per annum*), the return from FX fluctuation of the Yield-Differentials based (YDDIFF) timing signal was only 0.25% *per annum*.

The results for the regressions testing for the ability of the different long-neutral market-timing signals to generate *carry-alpha* are summarised in Table 5.2. The regressions show that all but one tested market-timing signals were able to generate positive *carry-alpha*. The *carry-alpha* of 4 long-neutral market-timing strategies was positive at a statistically significant level (these signals were USSP2, TEDSP, AVGSIGNAL, MAJVOTE). The only long-neutral market-timing signal which generated a negative *carry-alpha* parameter in the regression was the signal based on the yield-differentials time series (YDDIFF). With a p-value of 0.27, the negative *alpha* coefficient was not statistically significant. The *carry-beta* parameters exhibit statistically significant positive values for all long-neutral market-timing signals (see β-*column* in Table 5.2).

When we extend the factor model in Equation 4.19 for a market-timing term

γF_t^2 (see Equation 5.2), the statistically significant *alpha* coefficients dissappear, since the carry outperformance is now captured by the market-timing term (see Table 5.3). The market-timing coefficient γ is positive with a high statistical significance for VIX, USSP2, TEDSP, RISKM, MAJVOTE and AVGSIGNAL. Only in the case of the YDDIFF-indicator does the market-timing coefficient assume a statistically significantly negative value.

Market-Timed FX Carry Portfolios (Long-Short Setting) The performance metrics listed in Table 5.1 show that when the market-timing signals are allowed to generate long and short positions in the FX carry trade, the results deteriorate with respect to the long-neutral market-timing strategies. In the long-short setting only 1 out of 7 market-timing signals could outperform the long-only *Benchmark FX Carry Portfolio*. This market-timing signal is based on the 2-Year U.S. Swap Spread (USSP2), which already performed best in the long-neutral setting.

As in the long-neutral setting, the simple market-timing signals which generated the best results in terms of Sharpe ratio, are based on the liquidity-related risk factors: The 2-Year U.S. Swap Spread based timing signal (USSP2) produced a Sharpe ratio of 0.91 and the Ted Spread based timing signal (TEDSP) produced a sharpe ratio of 0.55. The volatility-based timing signals still generated positive Sharpe ratios of 0.20 in the case of the S&P 500 Volatility Index based timing signal (VIX) and 0.28 in the case of the RiskMetrics carry portfolio Volatility based timing signal (RISKM), but these are substantially lower than the long-only *Benchmark FX Carry Portfolio* which exhibited a Sharpe ratio of 0.64. The Sharpe ratio of the Yield-Differentials based indicator (YDDIFF) assumed a negative value of -0.03.

As in the long-neutral setting, the composed market-timing signals produced results which were comparable to the best single market-timing signals. The Majority-Vote based timing signal (MAJVOTE) produced a Sharpe ratio of 0.58 and the Average-Signal based timing signal (AVGSIGNAL) a Sharpe ratio of 0.57.

The four best performing timing signals in terms of Sharpe ratio were the ones able to produce a substantial amount of their return from currency fluctuations. These foreign exchange returns even exceed those generated by the long-neutral timed FX carry portfolios (compare the 'r_{FX}^a'-column values in Table 5.1). The 2-Year U.S. Swap Spread based timing signal (USSP2) generated a higher FX

related return of 2.69% *per annum* in the long-short setting than in the long-neutral setting; the Ted Spread based timing signal (TEDSP) generated a higher FX related return of 1.09% *per annum* in the long-short setting than in the long-neutral setting; the Majority-Vote based timing signal (MAJVOTE) generated a higher FX related return of 1.07% *per annum* in the long-short setting than in the long-neutral setting; and the Average-Signal timing signal (AVGSIGNAL) generated a higher FX related return of 0.09% *per annum* in the long-short setting than in the long-neutral setting.

The long-short market timed carry strategies generated yield pickup between 1.40% *per annum* and 2.43% *per annum* during the relevant data period. This is substantially lower than in the long-neutral setting, since now positions which assume short trades in the carry trade are allowed. These positions generate a negative yield by construction. A further reason for the worse performance of the long-short market timing strategies is given by the higher transactions costs they generate relatively to the long-neutral market-timing strategies. While the overall level of transactions costs paid in the case of the long-neutral timed FX carry portfolios ranged between 0.37% *per annum* and 0.71% *per annum* during the whole backtesting period, the long-short strategies generated higher transactions costs ranging from 0.62% *per annum* and 1.32% *per annum*.

The results for the regressions testing for the ability of the different long-short market-timing signals to generate *carry-alpha* are summarised in Table 5.2. As in the long-neutral setting, the regressions show that all but one of the market-timing signals we tested were able to generate positive *carry-alpha*. The *carry-alpha* of 4 long-neutral market-timing strategies were positive at a statistically significant level (these signals were USSP2, TEDSP, AVGSIGNAL, MAJVOTE). The only long-neutral market-timing signal which generated a negative *carry-alpha* parameter in the regression was the signal based on the yield-differentials time series (YDDIFF). Except for the market-timing signal based on the YDDIFF-indicator, the *carry-beta* coefficients exhibited statistically significant negative values for the long-short market timed FX carry portfolios (see β-*column* in Table 5.2).

As in the long-neutral setting, when we extend the factor model in Equation 4.19 for a market-timing term γF_t^2 (see Equation 5.2), the statistically significant *alpha* coefficients disappear, since the carry outperformance is now captured by the market-timing term (see Table 5.3). The market-timing coefficient γ is positive with a high statistical significance for VIX, USSP2, TEDSP, RISKM,

MAJVOTE and AVGSIGNAL. The market-timing coefficient assumes a statistically significantly negative value only in the case of the YDDIFF-indicator.

5.5.2 Additional Considerations

Comprehensive Risk-Adjustments

The portfolios presented in this chapter aim at improving the performance of the *G10* FX carry trade by market-timing a simple FX carry trade portfolio. Thus, the appropriate benchmark for our approaches is the performance of a simple FX carry portfolio. As we discussed in Section 3.1.2, a good number of risk factors other than carry have been proposed for the FX markets. These other risk factors are: value, momentum and volatility. Considering these additional risk factors, the question arises whether our FX carry portfolios are outperforming the vanilla returns because they are loading on some risk factors and thus earning a risk premium to do so.

In order to evaluate this possibility, we have performed additional factor-regressions for two representative strategies, namely the *long-neutral* Majority-Vote market timing rule and the *long-short* Majority-Vote market timing rule. For each portfolio we have performed regressions on three distinct data-ranges, namely the full data-range (January 1999 - March 2010), a *pre-crisis* data-range (January 1999 - May 2007) and a *post-crisis* data-range (June 2007 - March 2010).

The regression results for the *long-neutral* Majority-Vote market timing rule are summarised in Table 5.4 - Table 5.6. The regression results for the *long-short* Majority-Vote market timing rule are summarised in Table 5.7 - Table 5.9.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.63	0.10
Carry	0.40	0.02	19.12	0.00
Momentum	0.18	0.02	11.11	0.00
Value	0.23	0.02	10.56	0.00
Volatility	0.12	0.04	2.56	0.01

Table 5.4: Comprehensive Risk-adjustment regression for the long-neutral market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.00	0.00	-0.34	0.73
Carry	0.97	0.02	62.98	0.00
Momentum	0.03	0.01	3.05	0.00
Value	-0.03	0.01	-2.36	0.02
Volatility	-0.09	0.03	-3.12	0.00

Table 5.5: Comprehensive Risk-adjustment regression for the long-neutral market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - May 2007)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	0.33	0.74
Carry	0.20	0.03	6.12	0.00
Momentum	0.13	0.03	5.13	0.00
Value	0.05	0.04	1.31	0.19
Volatility	0.02	0.07	0.27	0.79

Table 5.6: Comprehensive Risk-adjustment regression for the long-neutral market timed FX carry portfolio with the Majority-vote timing signal (June 2007 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.55	0.12
Carry	-0.19	0.04	-4.61	0.00
Momentum	0.37	0.03	11.07	0.00
Value	0.46	0.04	10.51	0.00
Volatility	0.23	0.09	2.54	0.01

Table 5.7: Comprehensive Risk-adjustment regression for the long-short market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - March 2010)

We now analyse the risk-adjustment regression results for the *long-neutral* Majority-vote market timing rule for the FX carry portfolio. Contrary to the regression which considered only the FX carry factor as explanatory variable (see Table 5.2), we observe a negligible alpha coefficient which is not statistically significant throughout all three datasets. The loadings on the FX carry factor are significantly positive throughout all three datasets. Somewhat surprisingly, the loading on the FX momenum factor are statistically significantly positive as well throughout all three datasets. The loadings on the value and volatility factors do not behave homogeneously on the three different datasets: While they are both statistically significantly positive on the full data sample, they are significantly negative when only the dataset ranging from January 1999 to May 2007 is considered. During the post-crisis dataset ranging from June 2007 to March 2010, these two factors are not statistically significant.

The comprehensive risk-adjustment regressions for the long-short Majority-vote market timing rule produce similar results to the long-neutral Majority vote timing rule described above (see Table 5.7 - Table 5.9). The market timed FX carry portfolios exhibit significantly positive loadings on the FX momentum factor

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.00	0.00	-0.40	0.69
Carry	0.94	0.03	30.27	0.00
Momentum	0.06	0.02	2.98	0.00
Value	-0.06	0.03	-2.40	0.02
Volatility	-0.18	0.06	-3.12	0.00

Table 5.8: Comprehensive Risk-adjustment regression for the long-short market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - May 2007)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	0.24	0.81
Carry	-0.60	0.07	-9.02	0.00
Momentum	0.26	0.05	5.11	0.00
Value	0.11	0.08	1.29	0.20
Volatility	0.03	0.13	0.26	0.80

Table 5.9: Comprehensive Risk-adjustment regression for the long-short market timed FX carry portfolio with the Majority-vote timing signal (June 2007 - March 2010)

on all three datasets. Also, the signs and significance of the factor loadings on the value and volatility factors still exhibit different behavior on all three datasets. The major difference between the long-neutral and the long-short market timing rules, is that the FX carry factor loadings exhibit mixed signs in the regressions for the long-short Majority-vote timing rule. In fact the loadings on the FX carry factor are negative both during the full data sample (January 1999 - March 2010) and during the post-crisis data sample (June 2007 - March 2010).

We have to note that as in Chapter 4, where we tested various asset allocation strategies for FX carry portfolios, the significant regression coefficients in Table 5.4 - Table 5.9 could be of a spurious nature. The risk factors could be picking up the part of the returns which should be attributed to market timing. In order to exclude this, we perform two additional regressions on the full data range. These additional regressions have all four FX return factors (i.e. carry, momentum, value and volatility) and additionally a market timing term as explanatory variables. As discussed in Section 5.4.2, the market timing term still consists of the squared FX carry returns. These additional regressions are summarised in Table 5.10 (for the long-neutral Majority-vote rule) and in Table 5.11

(for the long-short Majority-vote rule).

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.41	0.16
Carry	0.40	0.02	18.82	0.00
Carry Squared	0.16	0.47	0.33	0.74
Momentum	0.18	0.02	10.82	0.00
Value	0.23	0.02	10.26	0.00
Volatility	0.11	0.05	2.27	0.02

Table 5.10: Comprehensive Risk-adjustment with market-timing term (*Carry Squared*) regression for the long-neutral market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - March 2010)

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.00	0.00	1.35	0.18
Carry	-0.19	0.04	-4.47	0.00
Carry Squared	0.28	0.94	0.30	0.76
Momentum	0.36	0.03	10.79	0.00
Value	0.46	0.04	10.22	0.00
Volatility	0.22	0.10	2.27	0.02

Table 5.11: Comprehensive Risk-adjustment with market-timing term (*Carry Squared*) regression for the long-short market timed FX carry portfolio with the Majority-vote timing signal (January 1999 - March 2010)

The regression results summarised in Table 5.10 and Table 5.11 display statistically significant loadings on all four FX risk factors. Except for the case of the FX carry factor in the *long-short* setting, all these factor loadings are strictly positive. Most importantly though, the loading on the squared FX carry returns are not significant in both regressions. Thus, the market timing rules *de-facto* seem to generate exposure to the alternative risk factors momentum, volatility and value, instead of generating genuine alpha returns. The results in this section thus outline that the alpha that could be obtained by market timing FX carry portfolios is eroded when comprehensive risk adjustments are being performed. Thus, by timing the FX carry strategy we have effectively loaded on other risk factors.

Senitivities to Rolling and Parameter Choice

In order to obtain a deeper insight into the sensitivities of our backtesting results to the choice of the rolling procedure and the threshold parameter, we perform a set of backtests which cover a wide range of parameter choices. More specifically, we tested the results for

- all market timing signals used in this chapter,

- long-neutral and long-short market timing rules,

- rolling and fixed window parameter estimation and

- threshold levels ranging from 0.50 to 0.90.

The Sharpe-ratios for the 140 backtested FX carry portfolios are summarised in Table 5.12 - Table 5.15.

	0.50	0.60	0.70	0.80	0.90
VIX	0.86	0.71	0.69	0.81	0.81
Ted Spread	0.75	0.99	0.97	1.11	1.23
2 Yr. Swap Spread	1.32	1.19	1.16	1.04	1.11
Yield Diff.	0.08	0.27	0.38	0.34	0.34
Risk Metrics	0.68	0.73	0.81	0.93	0.49
Majority Vote	0.95	0.79	0.93	0.91	1.02
Avg. Signal	0.90	0.92	0.93	0.96	0.90

Table 5.12: Performance sensitivity analysis: Sharpe Ratios for various threshold levels for the long-neutral market timing rule estimated with a fixed and expanding window.

	0.50	0.60	0.70	0.80	0.90
VIX	0.27	0.19	0.20	0.41	0.53
Ted Spread	0.15	0.50	0.55	0.82	1.16
2 Yr. Swap Spread	0.85	0.83	0.91	0.85	1.06
Yield Diff.	-0.56	-0.23	-0.03	-0.08	-0.06
Risk Metrics	-0.04	0.14	0.28	0.46	0.07
Majority Vote	0.30	0.54	0.63	0.73	0.50
Avg. Signal	0.26	0.48	0.61	0.77	0.88

Table 5.13: Performance sensitivity analysis: Sharpe Ratios for various threshold levels for the long-short market timing rule estimated with a fixed and expanding window.

	0.50	0.60	0.70	0.80	0.90
VIX	0.47	0.72	0.83	0.90	0.95
Ted Spread	0.38	0.38	0.60	0.67	0.68
2 Yr. Swap Spread	1.05	1.11	1.01	1.13	0.94
Yield Diff.	0.28	0.16	0.23	0.34	0.32
Risk Metrics	0.72	0.75	0.77	0.83	0.59
Majority Vote	0.75	0.54	0.73	0.49	0.59
Avg. Signal	0.73	0.76	0.81	0.90	0.79

Table 5.14: Performance sensitivity analysis: Sharpe Ratios for various threshold levels for the long-neutral market timing rule estimated with a rolling window with a constant length of 52 weeks.

	0.50	0.60	0.70	0.80	0.90
VIX	0.47	0.72	0.83	0.90	0.95
Ted Spread	0.38	0.38	0.60	0.67	0.68
2 Yr. Swap Spread	1.05	1.11	1.01	1.13	0.94
Yield Diff.	0.28	0.16	0.23	0.34	0.32
Risk Metrics	0.72	0.75	0.77	0.83	0.59
Majority Vote	0.80	0.57	0.54	0.70	0.66
Avg. Signal	0.73	0.76	0.81	0.90	0.79

Table 5.15: Performance sensitivity analysis: Sharpe Ratios for various threshold levels for the long-short market timing rule estimated with a rolling window with a constant length of 52 weeks.

Analysing the Sharpe ratios for all permutations of parameters in Table 5.12 - Table 5.15, we do not detect a particular structure or a drastic breakdown in performance for a change in the parameters. Thus, we consider our analyses based on a fixed window estimation of the timing rules and a threshold level of 0.70, as robust.

5.6   Conclusion

In this chapter we developed market-timing signals using a series of risk indicators and backtested the performance of trading FX carry portfolios with these signals. At first glance, our results suggest that the scepticism about the feasibility of market-timing proclaimed by efficient market theorists (see Section 5.1.1) might be misplaced, since without permitting our analysis to turn into a data-mining

exercise 6 out of 7 market-timing signals were able to outperform the *Benchmark FX Carry Portfolio* in the long-neutral setting.

On the other hand only 1 out of 7 market-timing signals was able to outperform the long-only benchmark when allowing long as well as short positions in the FX carry portfolio. In fact, all market-timing signals exhibited a better risk-adjusted performance in terms of Sharpe ratio in the long-neutral setting than in the long-short setting. An intuitive explanation for this is that in the long-short setting the strategies accept to pay a riskless negative yield differential (or *carry*), in order to potentially improve the performance on the volatile FX return component. The precision of the timing of the FX return component would have to be even better than our indicators were able to achieve in order to successfully take long as well as short positions in the FX carry trade.

As far as the interpretation of the quality of specific risk factors for FX carry market-timing is concerned, we were able to identify the liquidity related indicators as the most profitable during our backtesting period. Contrary to our expectations (see Section 5.1.3), the novel yield differentials based timing indicator (YDDIFF) performed very poorly. This means that periods of relatively low interest rate differentials, i.e. periods which offer low yield-pickup in FX carry portfolios, are not necessarily bad for the carry trade performance and *vice versa*.

We partially confirm the results obtained by Dunis and Miao [2007] who showed that trading filters based on volatility proxies could improve the performance of FX carry strategies. The VIX and RISKM based timing signals produced enhanced trading results in terms of their Sharpe ratio in the long-neutral setting. Unlike Dunis and Miao [2007] we find that timing FX carry trades in a long-short setting produces poor results compared to the long-only benchmark and the long-neutral timed FX carry portfolios.

The aggregated market-timing signals (AVGSIGNAL and MAJVOTE) were shown to produce stable results. The performance of the aggregated timing signals were comparable to the best performing single indicators and did not suffer excessively from the inclusion of poorly performing timing indicators (e.g., YD-DIFF). These results provide some justification for efforts undertaken by the industry to construct aggregated risk indicators for foreign exchange market timing (see Section 5.1.3). As such, our findings contradict those of Vesilind [2006], who stated that timing the FX carry trade with aggregated risk indicators does not produce enhanced trading results.

A visual analysis of the market-timing signals (see Figure 5.3) clarifies that

the major performance improvement comes from successfully timing the FX carry drawdown associated with the recent credit crisis. In our dataset, the drawdowns incurred by the FX carry trade before the credit crisis would have been very small. Thus, we have to question whether our market-timing strategies would have been used in practice, since the performance of the long-neutral FX carry portfolio would have been difficult to beat during the period from 1999 to 2007. Also, including liquidity related risk factors (such as the Ted spread *TEDSP* and the 2 year swap spread *USSP2*) for timing the FX carry trade is a much easier decision today than it was before the credit crisis.

We conclude that timing the FX carry trade in a long-neutral setting promises to enhance FX carry trade performance and that market-timing signals based on aggregated risk factors produce robust results which are comparable to the best single risk factors. Nevertheless we notice a lookback bias in our selection of risk factors, since before the credit crisis we would probably have put a greater emphasis on volatility related time series at the cost of the liquidity proxies. To overcome the risk of considering inappropriate risk indicators in the future, we advocate a broader diversification of risk proxies when constructing the aggregated market-timing signals.

Chapter 6

Carry Trade Money Management

6.1 Introduction

In this chapter we will study how different models for determining leverage levels affect the performance of the FX carry trade. Such a study is relevant since it has been shown that FX traders typically execute the FX carry trade with leverage (see Section 6.1.1). Since the seminal work by Kelly [1956] financial practitioners and gamblers have become aware of the important effect that leverage has on the final performance of trading and gambling strategies (see Section 6.1.3). In the following sections, we aim at providing an overview of existing literature on leveraged FX carry trades and money management methodologies (i.e. optimal leverage models). Subsequently, with our empirical analyses we contribute to the very limited empirical research available on optimal leverage models for trading systems. We will show how the choice of the leverage model substantially affects the final performance of FX carry portfolios. Also, we expose the weaknesses of the Sharpe-ratio as a performance metric, when it comes to assessing the capital growth of leveraged trading strategies. In order to address the shortcomings of the Sharpe-ratio, a novel performance metric will be introduced (see Section 6.4.4).

6.1.1 The Carry Trade and Leverage

Literature provides indications that FX carry trades are often executed with leverage (see Gagnon and Chaboud [2007] and Galati et al. [2007b]). Motivated by this evidence Darvas [2009] analysed the impact of different levels of leverage on the performance of FX carry trading strategies on a monthly dataset from January 1976 to April 2008. Darvas [2009] found that the risk adjusted performance of

FX carry strategies decreases with increasing levels of leverage. Most FX carry strategies went bankrupt when large leverage levels were applied. Darvas [2009] concluded that the forward rate bias inefficiency (see Section 3.2.3) is dependent on the selection of the level of leverage by the investor.

We do not agree with this conclusion reached by Darvas [2009]. The fact that excessive leverage can cause bankruptcy is a well known consequence of overinvesting (i.e. bad money management) and is independent of the underlying return process.

6.1.2 Empirical Applications of Kelly Criterion in Finance

Despite the good theoretical treatment of the Kelly criterion in literature, we find few empirical studies which analyse the effects of money management techniques on the profitability of trading strategies.

Wetzer [2003] applied various money management methodologies for calculating the position sizes of trading systems based on technical trading rules and ARIMA forecasts. By analysing the profits and losses of 280 trading systems Wetzer [2003] showed that money management has the potential to alter the profitability of trading systems more than a market-timing signal. Wetzer [2003] concluded that money management should play a bigger role in finance and quantitative trading systems development.

Anderson and Faff [2004] tested the performance of a simple technical trading rule on five futures markets. The position sizes were computed via the *optimal f* methodology proposed by Vince [1990]. [1] Similarly to Wetzer [2003], Anderson and Faff [2004] found that the performance of the trading strategy is dramatically influenced by the money management strategies. Anderson and Faff [2004] concluded that money management plays a more important role in trading rule profitability than previously considered.

6.1.3 The Kelly Criterion

Money Management is concerned with the determination of the optimal amount of capital to invest in trading situations with positive expected returns. In his seminal paper, Kelly [1956] presented a criterion for optimising the betting size

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[1] The optimal-f money management technique consists in numerically optimising the fraction of capital to risk in a given trade, such that the unconditional expected geometric return of the trading strategy is maximised (see Vince [1990]).

when gambling with an informational advantage over the bookmaker. Kelly's concepts have been understood very quickly by the gambling community. The first published system for beating the casino game of Blackjack (see Thorp [1962]) was based on a combination of card counting techniques and a variable bet sizing methodology based on Kelly's criterion.[2]

Kelly recognised that a gambler should address two main objectives when determining the optimal amount of capital to place on a specific bet. These objectives are expected return maximisation on one hand, and capital preservation on the other hand. Both objectives represent a tradeoff. The expected return of a bet with positive expectancy is maximised by betting the maximum possible amount. But betting a too large amount would almost surely cause the gamblers ruin since, no matter how large his edge might be, in the long run he would lose his entire capital during a sequence of losing bets. The Kelly criterion (see Kelly [1956]) solves the return-security tradeoff by determining the optimal amount of capital to put at stake such that the long term capital growth is maximised.[3]

The wealth distribution generated by sizing bets according of the Kelly criterion has been shown to possess positive characteristics. MacLean et al. [1992] proved that the expected wealth generated by the Kelly strategy is superior to the wealth produced by any other money management system, Hakansson and Miller [1975] showed that the Kelly strategy never risks ruin, and Algoet and Cover [1988] showed that the Kelly strategy minimises the expected time to achieve a given investment objective.

On the other hand, managing position sizes according to the Kelly criterion also entails some drawbacks for real-world investment situations. Following Thorp [2006], the Kelly strategy can be very risky in the short term. Several studies (see e.g. Kahneman and Tversky [1979], Ert and Erev [2008] and Kahneman et al. [1990]) have demonstrated that the human brain associates a larger relevance to the experience of losses versus the experience of gains. Thus, the high level of risk inherent to Kelly position sizing models, would cause investors to prefer other investment opportunities trading some of the expected wealth generated by the Kelly strategy against more security. The utility function that leads to the Kelly criterion would only be suitable for investors with an absolutely risk-neutral

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[2]Poundstone [2005] contains a popular treatment of the application of the Kelly criterion in gambling and finance.

[3]The focus on long term performance differentiates the Kelly criterion from *Modern Portfolio Theory* MPT, which is based on optimal one-period investment decisions (see Markowitz [1952]).

attitude to risk, and is thus not appropriate for most subjects.

Moreover, MacLean and Ziemba [1999] noted that the optimal position sizes computed by the Kelly strategy are sensitive to estimation errors in the model inputs, and that investing more than the optimal amount lowers the expected capital growth while increasing risk.

A practical solution to the danger of overinvesting and the high volatility inherent to the Kelly strategy, would be to trade growth for security through investing only a fraction of the optimal Kelly position size. Some authors propose to invest half of the optimal Kelly-amount, while others even advocate to size the position down to one fourth of the optimal Kelly position size (see McDonnell [2008] and Thorp [2006]).

Formalizing the Kelly Criterion In the following we will formalise the intuition behind the Kelly criterion. Firstly, we define a random variable H_t as the percentage of the current amount of capital C_t relative to the previos period capital C_{t-1}. Furthermore, the return on the capital in period t is modeled as the position size f multiplied with a random variable R_t, whose distribution will not be specified here.

$$H_t = \frac{C_t}{C_{t-1}} = 1 + fR_t \tag{6.1}$$

If in $t = 0$ an investor had a given amount of capital C_0, and was to play this investment game a given number of periods T while reinvesting the previous periods winnings, his final capital C_T would amount to:

$$C_T = C_0 \prod_{t=1}^{T} H_t \tag{6.2}$$

The objective of the Kelly criterion is to maximise the long-run rate of capital growth. By rearranging $C_T = C_0 e^{TG_T}$, we define the exponential rate of growth of the capital G_T as:

$$G_T = \frac{1}{T} log(\frac{C_T}{C_0}) \tag{6.3}$$

By inserting Equation 6.2 into Equation 6.3, we get:

$$G_T = \frac{1}{T} \sum_{i=t}^{T} log(H_t) \tag{6.4}$$

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If we assume that the random variables $H_{t=1,..,T}$ form a sequence of independent and identically distributed random variables, we can apply the law of large numbers and find:

$$\lim_{T \to \infty} G_T = E[log(H)] \tag{6.5}$$

Thus, in order to maximise the growth function

$$g(f) = E[log(H(f))] \tag{6.6}$$

with respect to f, we set

$$\frac{dg}{df} = 0. \tag{6.7}$$

Solving this term for f yields the optimal fraction of capital f^* to put at risk.

The Traditional Kelly Formula The first Kelly formulas for determining growth-optimal betting sizes f^* were presented by Kelly [1956] and, in a more general way, Thorp [1969]. These 'traditional' Kelly formulas are suitable for bets with two distinct outcomes (WIN and $LOSE$), known probabilities for these outcomes (p_{WIN} and $p_{LOSE} = 1 - p_{WIN}$) and a fixed payout ratio B, defined as the ratio of the amount won in case of a successful bet to the amount wagered for that bet. In that case the random variable R_t (see Equation 6.1) is:

$$R_t = (1 + B)X_t - 1 \tag{6.8}$$

where $P(X = 1) = p_{WIN}$ and $P(X = 0) = p_{LOSE}$. The corresponding growth function is given by (see Thorp [1969]):

$$g(f) = p_{WIN} ln(1 + fB) + (1 - p_{WIN}) ln(1 - f). \tag{6.9}$$

We can easily compute $\frac{dg}{df}$ by applying the chain rule. Solving $\frac{dg}{df} = 0$ for f yields the well known Kelly formula:

$$f^* = p_{WIN} - \frac{1 - p_{WIN}}{B} \tag{6.10}$$

In his original paper, Kelly [1956] presented the derivation for the special case where the payoffs of winning and losing are equal (i..e $B = 1$): The solution to this case is nested in the more general Equation 6.10:

$$f^* = p_{WIN} - p_{LOSS} \tag{6.11}$$

The Kelly Formula for Gaussian Return Distributions In the financial markets, an investment typically has many potential outcomes rather than just a few.[4] Thus, the popular Kelly formulas presented above (Equation 6.10 and Equation 6.11) are not ideally suited for the domain of securities trading. This leads to the use of continuous instead of discrete probability distributions. Thorp [2006] derived a solution for the Kelly formula which assumes normally distributed securities returns and accounts for a risk free interest rate i. The random variable H in a specific period t would then be modelled as:

$$H_t = 1 + (1 - f)i_t + fR_t, \tag{6.12}$$

where i_t is the available risk free interest rate at time t and $R_t \sim \mathcal{N}(\mu_t, \sigma_t^2)$. Following Thorp [2006], the growth function for such a process can be approximated by:

$$g(f) = i + f * (\mu - i) - \frac{\sigma^2 f^2}{2} \tag{6.13}$$

The growth-optimal position size f^* can then be computed by solving

$$\frac{dg}{df} = \mu - i - \sigma^2 f = 0, \tag{6.14}$$

i.e.:

$$f^* = \frac{\mu - i}{\sigma^2} \tag{6.15}$$

6.2 Contributions

According to Ziemba [2003], the two central aspects of an investment strategy are a) when to invest (i.e. signal generation) and b) how much to invest (i.e. money management). Chapter 4 and Chapter 5 focused on optimal ways to implement FX carry trades and thus address the signal generation aspect of the strategy. In the remainder of this chapter we will examine the effect of different money management methodologies on the profitability of FX carry portfolios.

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[4]An exception being the trading of derivatives with a binary payout, e.g. *digital options*.

The first part of our empirical analysis consists in testing the performance of FX carry portfolios traded with constant leverage levels ranging from 0.5 to 10, a methodology similar to the one adopted by Darvas [2009]. We will select three constantly-leveraged FX carry portfolios and use them as benchmarks to assess adaptive time-varying leverage models based on the Kelly criterion (see Section 6.4.2). Furthermore, the sequential backtest of constantly leveraged FX carry portfolios will serve as an illustration of the effects that leverage can have on trading performance.

The following empirical research adds to the limited body of research quantifying the impact of money management strategies on trading strategy performance. Furthermore, this research expands on research initiated by Darvas [2009] on the effects of leverage on the returns generated by professional FX managers. The performance of leveraged FX carry strategies during the recent credit crisis should offer new insights into the maximum leverage which FX carry portfolios can withstand during periods with high drawdowns.

In Section 6.4.2 we propose extensions to the Kelly formula for gaussian return processes. The extensions allow for a practical management of the problems of overinvesting and high short-term risk inherent to the Kelly strategy.

6.3   Data

We perform simulations of leveraged FX carry portfolios on a weekly data set from 10.12.1999 to 05.03.2010. In the following, we briefly outline the data base for the research in this chapter.

6.3.1   The Benchmark FX Carry Portfolio

The starting point for the analyses of our dynamical position sizing algorithms is the *Benchmark FX Carry Portfolio*. Details concerning the raw data sources, the methodology and the performance of the *Benchmark FX Carry Portfolio* are outlined in Appendix A.

The portfolio yield differentials inherent to the *Benchmark FX Carry Portfolio* (see Section A.5), as well as the *RiskMetrics* conditional volatility estimates of this portfolio (see Section A.5) will serve as central inputs for the money management methodology outlined in Section 6.4.2.

6.3.2 Risk Indicators

The risk indicators 2-Year U.S. Swap Spread (USSP2), Ted Spread (TEDSP) and CBOE S&P 500 Volatility Index (VIX) will serve as inputs for the construction of confidence measures for FX carry trade profitability (see Section 6.4.3). For a detailed description of these time series we refer to Section 5.3.2.

6.4 Methodology

6.4.1 Constant Leverage Levels for FX Carry Trading

We will compute the performance of FX carry portfolios with constant leverage levels ranging from 0.5 to 10 in 0.5 increments. Thus, we apply the methodology proposed by Darvas [2009] on the *Benchmark FX Carry Portfolio* (see Appendix A). The portfolio weights to these leveraged FX carry strategies will be computed according to:

$$\mathbf{w}_{t,f}^{BMCP} = f * \mathbf{w}_t^{BMCP} \tag{6.16}$$

Where $\mathbf{w}_{t,f}^{BMCP}$ denotes the current vector of portfolio weights for a given leverage level f ($f = 0.5, 1, 1.5, ..., 10$), and $\mathbf{w}_t^{BMCP}$ denotes the current portfolio weights vector of the simple *Benchmark FX Carry Portfolio* (see Section A.2). The leveraged FX carry portfolio performance will then be computed according to the methodology described in Section A.3 and Appendix B.

6.4.2 A Time-varying Leverage Model based on the Kelly Formula

We propose a time-varying leverage model based on the Kelly formula for continuous gaussian return processes (see Equation 6.15). Since FX carry portfolios are fully self financed, we can omit the risk free interest rate i_t from Equation 6.15 and get:

$$f_t^* = \frac{\mu_t}{\sigma_t^2} \tag{6.17}$$

Since we keep the assumption of the spot exchange rates following a random walk, the expected FX carry portfolio returns $\hat{\mu}_t$ consist of the yield differentials of

the *Benchmark FX Carry Portfolio* in each week t (see Section A.5). We estimate the FX carry portfolio variances $\hat{\sigma}_t^2$ by the *RiskMetrics* exponential smoothing methodology (see Section A.5).

In order to allow for a more conservative strategy than the Kelly criterion, we extend the money management formula to allow for fractional Kelly position sizing, as advocated by some authors in literature (see Section 6.1.3). This is achieved by multiplying the f_t^*'s by a constant risk appetite factor c ($0 \leq c \leq 1$).

Errors in the estimation of the input parameters of the Kelly formula can lead to overinvesting (see Section 6.1.3). We address this problem by weighting the expected returns for the FX carry portfolio $\hat{\mu}_t$ by the confidence measures $\kappa_{I,t}$, with $0 \leq \kappa \leq 1$. These confidence measures will assume small values when the FX carry portfolio is expected to perform badly, and large values when the FX carry portfolio is expected to perform well. We will discuss our choice for the κ factors in Section 6.4.3.

Thus, the extended money management formula based on the Kelly criterion becomes:

$$f_t^*(I, c) = \frac{\hat{\mu}_t \kappa_{I,t}}{\hat{\sigma}_t^2} c \tag{6.18}$$

We test 15 time-varying leverage models for all combinations of $c = (\frac{1}{4}, \frac{1}{2}, 1)$ and $I = (NAIVE, USSP2, TEDSP, VIX, AVG)$ on the *Benchmark FX Carry Portfolio*. The portfolio weights of the *Benchmark FX Carry Portfolio* will be multiplied by the leverage levels computed by Equation 6.18:

$$\mathbf{w}_t^{BMCP}(I, c) = f_t^*(I, c) * \mathbf{w}_t^{BMCP} \tag{6.19}$$

The leveraged FX carry portfolio performance will then be computed according to the methodology described in Section A.3 and Appendix B.

Figure 6.1 depicts the optimal time-varying leverage levels for all confidence measures and $c = 1$.

The Normality Assumption in Dynamical Leverage Models The assumption of normally distributed returns for financial market data is typically not confirmed by empirical financial data. Stylised facts about financial returns which are not accurately described by a gaussian distribution include heavy tails, gain/loss asymmetries and volatility clustering (see e.g. Cont [2001]).

So how can the application of Equation 6.18 for determining growth-optimal

PANEL A

PANEL B


PANEL C
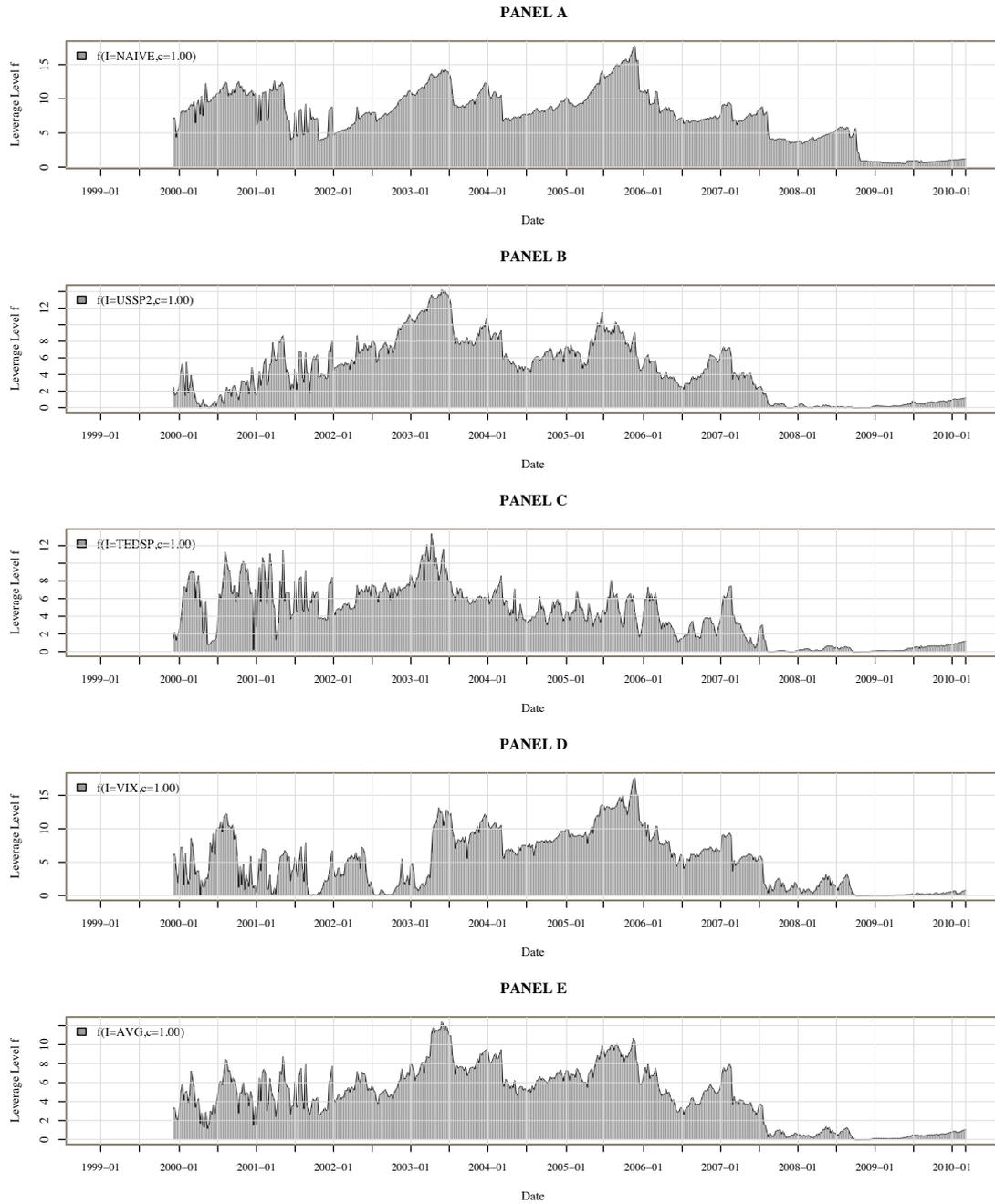
PANEL D

PANEL E

Figure 6.1: Time-varying Leverage Levels computed according to $f_t^*(I, c) = \frac{\hat{\mu}_t \kappa_{I,t}}{\hat{\sigma}_t^2} c$ with the Parameters $I = NAIVE$ and $c = 1$ (PANEL A); $I = USSP2$ and $c = 1$ (PANEL B); $I = TEDSP$ and $c = 1$ (PANEL C); $I = VIX$ and $c = 1$ (PANEL D); $I = AVG$ and $c = 1$ (PANEL E).

leverage sizes be justified, given that it originates from the assumption of normally distributed returns?

As we have outlined in Section 6.1.3, Thorp [2006] derived the analytical solution to the Kelly criterion for normally distributed returns. [5]

Thus, the main advantage in assuming normally distributed returns, is that this assumption allows for an elegant analytical solution to the Kelly criterion. The closed form solution to the Kelly formula for gaussian returns allows us to empirically test and analyse conditional optimal leverage techniques instead of relying on historical unconditional data, thereby contributing to the limited empirical literature on the subject.

Nevertheless, we argue that as conditional dynamic leverage models become more established in literature, future research should aim at studying these techniques based on returns distributions which more appropriately describe asset price returns. An interesting approach on the Kelly criterion with alternative returns distributions has been presented by Osorio [2008], who investigated the effect of fat-tails and investor risk aversion on optimal leverage levels. Osorio [2008] developed a procedure for determining the optimal Kelly-leverage for t-distributed returns, since the t-distribution matches empirical properties of financial time series such as positive excess kurtosis, a power-law tail behavior, and near-normal behavior in the central part of the probability distribution function. In his numerical experiments Osorio [2008] finds that the optimal leverage levels of the Kelly model are lower when the tails of the distribution are fatter or the investors level of risk aversion increases. Nevertheless, Osorio [2008] does not provide trading strategy simulations based on his optimal conditional leverage model.

6.4.3 Confidence Measures for FX Carry Trade Profitability based on Risk Factors

In the following we describe how we construct the confidence measures which will be used as κ inputs to the time varying money management formula Equation 6.18 (see Section 6.4.2).

The three risk indicators (see Section 6.3.2) are processed into rolling p-values

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[5]As other popular models used in mathematical finance are often based on the assumption of normally distributed returns for analogeous reasons (e.g. Modern Portfolio Theory (Markowitz [1952]), the Black-Scholes options pricing model (Black and Scholes [1973]) or the Black-Litterman portolio optimisation model (Black and Litterman [1992]).

ϕ according to the methodology described in Section 5.4.1. In order to represent a suitable confidence measure for the profitability of FX carry trades κ, we perform the following computations:

$$\kappa_{I,t} = 1 - \phi_{I,t} \tag{6.20}$$

Where I indicates the risk indicator ($USSP2$,$TEDSP$ or VIX) and t is the actual time-period. Furthermore, we compute an aggregated confidence measure κ_{AVG} by taking the average confidence measure of the three risk indicators:

$$\kappa_{AVG,t} = \frac{\kappa_{USSP2,t} + \kappa_{TEDSP,t} + \kappa_{VIX,t}}{3} \tag{6.21}$$

Also, we define a naive confidence measure ($I = NAIVE$) which will assume a constant value of 1:

$$\kappa_{NAIVE,t} = 1 \tag{6.22}$$

The values of the confidence measures κ are by construction bounded between zero and unity. We expect low values in the confidence measures to coincide with periods of FX carry trade underperformance. Conversely high confidence measure values should coincide with positive FX carry returns.[6]

For this piece of research we have chosen to utilise confidence measures based on the risk factors used for the carry timing analyses performed in Chapter 5. The test results which were discussed in Chapter 5 (see Section 5.5) showed, that most of the risk indicators were able to outperform the long-only FX carry portfolio. In order to mantain a coherent framework we thus integrate these indicators as heuristic confidence measures in this chapter. We note that probabilistic forecasting models[7] would be formally more adequate since they are able to directly model the probability of the FX carry trade perfroming well in the next period. We thus point out that such models should be considered for further research and in extensions of our proposed approach.

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[6]For a discussion on the expected relationship between the risk indicators and FX carry trade returns we refer to Section 5.1.3.

[7]E.g. Logit/Probit Models (see Hosmer and Lemeshow [2000]), Nearest Neigbour Models (see Bishop [2006]) and Artificial Neural Networks (see Zimmermann and Rehkugler [1994]).

6.4.4 A Performance Measure for evaluating Capital Growth with respect to Risk

In this section we aim to introduce a novel performance metric which addresses some of the shortcomings of the Sharpe ratio (see Section B.3). The Sharpe ratio constitutes a standard risk-adjusted performance measure for trading strategies. Since its computation is based on arithmetic mean returns, it is not suitable for assessing the long term growth potential of trading strategies. The Sharpe ratio performs a risk adjustment by dividing the excess returns by the standard deviation of returns. Arguably, the standard deviation does not consititute an appropriate measure of risk for trading strategies since asset returns have been shown not to follow a gaussian distribution (see Cont [2001]).

We postulate that an enhanced performance metric should be able to assess the performance of alternative position sizing methodologies by considering capital growth (i.e. the geometric mean return) as well as adjusting for risk in order to reflect the risk-aversion ordinarily displayed by speculators (see Kahneman et al. [1990]). Naturally, we would expect the performance measure to be increasing with respect to the capital growth. Also, the performance measure should decrease with respect to capital losses and risk. Following prospect theory (see Kahneman and Tversky [1979]), the utility function that speculators possess with regards to capital losses is convex. To embody this feature, the second derivative of the performance measure with respect to losses should be strictly positive.

Moreover, the same underlying trading strategy should display different performance metrics for changing constant leverage levels, since the absolute level of leverage affects the properties of a given trading strategies wealth distribution (see e.g. Darvas [2009]). As we will confirm in the empirical results throughout the following sections, the Sharpe ratio fails to satisfy this requirement, since leverage affects the arithmetic return and the standard deviation linearly and with the same multiplier.

As a proxy for the risk of a trading strategy we choose the maximum drawdown measure (see Section B.5). The maximum drawdown measure constitutes an arguably better risk measure than the standard deviation, since it does not suffer from the drawbacks associated with the stylised facts observed in financial data as the non-normality of asset returns and potential serial correlation within those returns (see e.g. Alexander and Baptista [2006]). We consider the maximum

drawdown measure as particularly appropriate since it accurately measures how much capital has been lost by a trading strategy during its the worst losing streak. Also, the maximum drawdown is capped at unity. When a trading strategy exhibits a maximum drawdown of unity, the maximum capital that was lost by that trading strategy was 100%. In such a case the strategy went bankrupt and the performance measure should discard the trading strategy.

In order to assess the performance of the leveraged FX carry portfolios under consideration of their growth potential and their risk as measured by the maximum drawdown while satisfying all of the features described above, we define a novel performance measure *drawdown-adjusted-growth* (DAG) as:

$$DAG = \max(-log(MAX.DD) * r^g, 0) \tag{6.23}$$

Where r^g is the annualised geometric return of the strategy and $MAX.DD$ denotes the maximum drawdown in percent.[8] The performance measure in Equation 6.23 has the following desirable properties:

- DAG rises as the geometric return r^g rises, i.e.
  $\frac{dDAG}{dr^g} > 0 \ \forall r^g >= 0$.

- DAG falls as the maximum drawdown rises, i.e.
  $\frac{dDAG}{dMAX.DD} < 0$.

- The second derivative of the DAG with respect to losses is strictly positive
  $\frac{d^2DAG}{dMAX.DD^2} > 0$.

- DAG assumes a zero-value when the strategy leads to bankruptcy, i.e.
  $DAG(MAX.DD = 1.00) = 0$.

- DAG assumes a zero-value when the strategy exhibits a negative capital growth, i.e.
  $DAG(r^g <= 0) = 0$.

- DAG approaches infinity if the growth is positive and the maximum drawdown approaches zero, i.e.
  $\lim_{MAX.DD \to 0} DAG(GR > 0, MAX.DD) = \infty$.

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[8]See Appendix B for the methodology behind the computation of the geometric return and the maximum drawdown metrics.

The DAG performance measure severely penalises large drawdowns and volatility while rewarding capital growth. Thus, the DAG represents a methodology for evaluating trading strategies according to risk-adjusted-growth. DAG values of zero indicate that the strategy will invariably lead to bankruptcy in the long run and should therefore not be implemented in practice.

6.4.5 Statistical Tests for Carry-Alpha and Market-Timing Ability

Analogeous to the methodology adopted in Chapter 4 and Chapter 5, we will benchmark the different money management methodologies against the Benchmark FX carry portfolio (see Appendix A). In order to test for the existence of *carry-alpha*, we will run regressions of the form $R_t = \alpha + \beta F_t + \epsilon_t$, outlined in Section 4.4.4. Furthermore, we will test for the existence of a market-timing effect in the money management models by estimating regressions of the form: $R_t = \alpha + \beta F_t + \gamma F_t^2 + \epsilon_t$, outlined in Section 5.4.2.

6.5 Empirical Results

6.5.1 Constant Leverage Levels

In this section we will present the results of sequentially backtesting FX carry portfolios with different constant leverage levels.

Figure 6.2 depicts the development of 100 EUR starting capital invested in the constantly leveraged FX carry portfolios. Figure 6.2 visualises the effect that overleveraging can have on the equity curve of a trading strategy: During periods of stable and positive returns, highly leveraged strategies will generate very high absolute returns. The FX carry strategy with a constant leverage of 10 reached a maximum equity of $20,900.50$ EUR on the 20th of July 2007. On the other hand overinvesting will, in the long run, cause large equity drawdowns and in the worst case bankruptcy. We already ascertained that the FX carry trade suffered a high drawdown phase during the credit crisis (see Section 4.6 and Section A.3). Figure 6.2 visualises the dramatic effect of this drawdown phase on the equity of the highly leveraged FX carry strategies. At the end of our backtesting period on the 05th of March 2010 the equity of the FX carry portfolio with a constant leverage level of 10 was only at 15 EUR (i.e. the strategy lost 99.93% from its

peak on the 20th of July 2007).
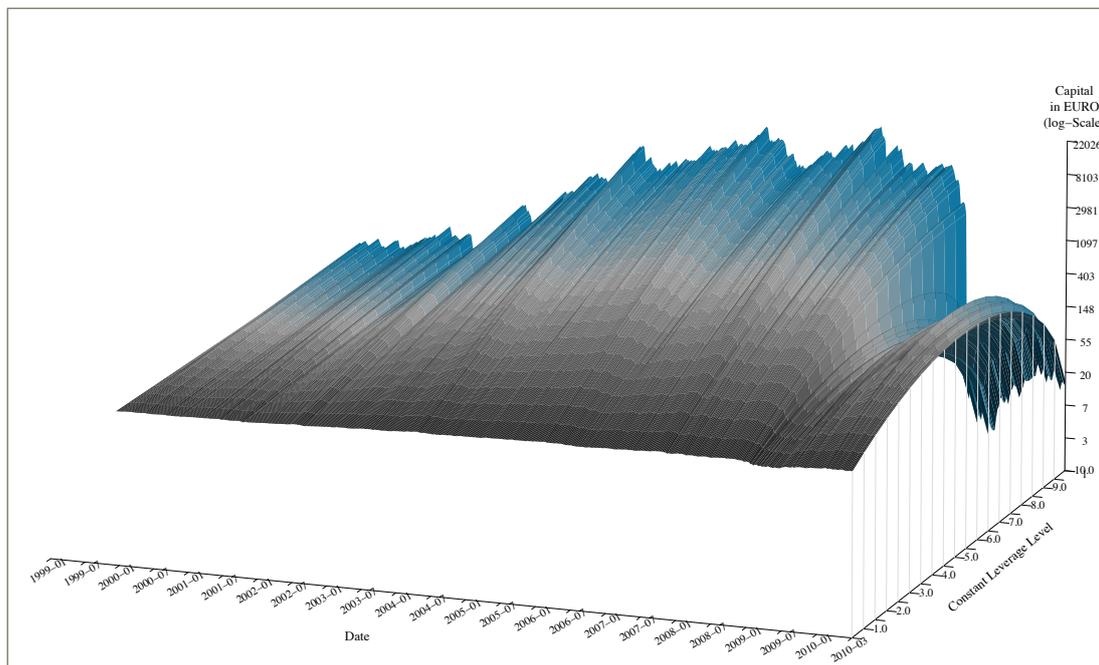
Figure 6.2: Capital Growth of 100 EUR for FX Carry Portfolios with Constant Leverage Levels f=0.50, 1.00, 1.50, ..., 10.00.

Figure 6.3 depicts the annualised geometric returns GR (PANEL A), the maximum drawdown measures $MAX.DD$ (PANEL B) and the DAG measures (PANEL C) of the constantly leveraged FX carry portfolios. The performance metrics in Figure 6.3 quantify the effect that different leverage levels had on the FX carry portfolios performance during our backtesting period from. The highest capital growth would have been generated by the FX carry portfolio with a constant leverage level of 5.5 (see Figure 6.3, PANEL A). Portfolios with a higher leverage than 5.5 would have produced a smaller capital growth at a higher risk than the portfolios with a lower leverage than 5.5. Leverage levels over 9 would have generated a negative capital growth, even though the unleveraged FX carry portfolio strategy exhibited a positive mean return. PANEL B of Figure 6.3 depicts the maximum drawdowns for the different leverage levels. As visualised by the equity lines in Figure 6.2, the drawdowns increase as the leverage increases. The highest leverage levels generate maximum drawdown levels very near to unity (which would signify total loss of capital). In PANEL C of Figure 6.3, the risk-adjusted performance measure drawdown-adjusted-growth DAG (see Section 6.4.4) is depicted in relation to the applied leverage levels. We find

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the maximum value of the DAG at a constant leverage level of 1.5.

This sequence of backtests thus exemplifies the reason behind the propagation of fractional Kelly approaches by various authors (see Section 6.1.3). The parabolic form of the growth function $g(f)$ in PANEL A of Figure 6.3 offers an intuitive understanding of the Kelly criterion: A positive expectancy strategy has a specific optimal fraction f^* which generates maximum wealth over time. Over-leveraging would be highly inefficient, since a) a lower geometric return will be achieved (see PANEL A in Figure 6.3) and b) this lower return could be achieved by adopting a lower risk (see PANEL A and PANEL C in Figure 6.3). The risk-adjusted DAG measure provides a methodology for selecting portfolios with high growth rates and low risk as measured by the maximum drawdown metric.
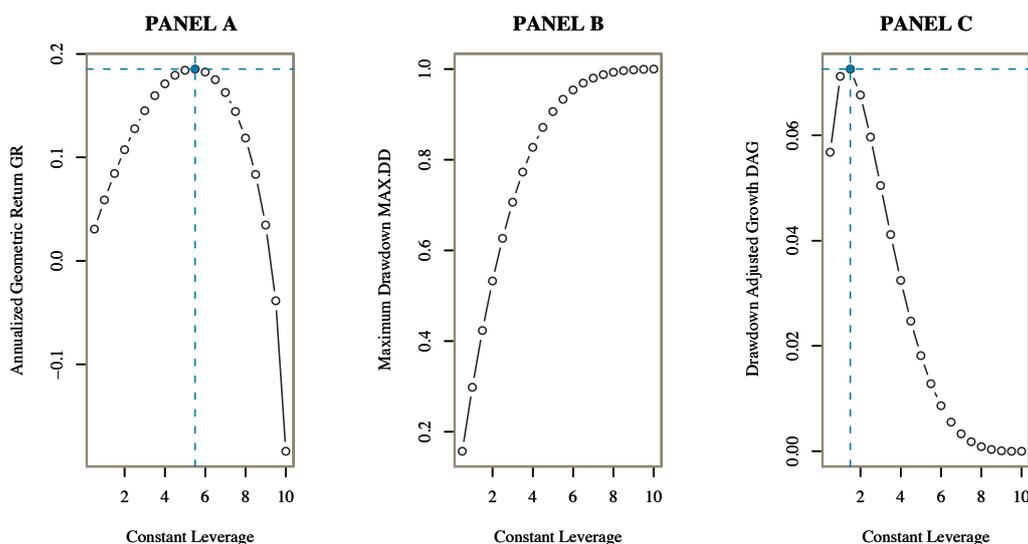
Figure 6.3: Performance Metrics for the FX Carry Portfolios with Constant Leverage Levels (PANEL A: Annualised Geometric Return GR; PANEL B: Maximum Drawdown $MAX.DD$; PANEL C: Drawdown Adjusted Growth DAG).

We select three constantly leveraged FX carry portfolios for further comparison with the time-varying leverage models (see Section 6.5.2). These portfolios have constant leverage levels of:

- 1.0 : This is the standard leverage level used in the previous chapters of this research.

- 1.5 : This is the constant leverage level with the highest DAG measure.

- 5.5 : This is the constant leverage level with the highest growth rate as measured by the annualised geometric return.

We stress that the leverage levels 1.5 and 5.5 are selected with hindsight. Nevertheless we will use them as benchmarks to assess the time-varying leverage models.

6.5.2 Time-varying Leverage Levels

Table 6.1 summarises the average leverage level f_{AVG} and the performance metrics annualised geometric return GR, maximum drawdown $MAX.DD$, drawdown-adjusted-growth DAG and Sharpe ratio SR inherent to the FX carry portfolios traded with the time-varying leverage model and 3 constant leverage money management models. The equity lines resulting from applying the time-varying leverage levels to the FX carry portfolio are depicted in Figure 6.4.

An analysis of the performance metrics in Table 6.1 reveals that the Kelly based money management models performed better than the FX carry portfolios with constant leverage levels. Most Kelly based money management models generated higher annualised geometric returns than the constant leverage models. An assessment of the money management strategies according to the risk adjusted performance measures drawdown-adjusted-growth DAG and Sharpe ratio SR results in an even clearer outperformance of the Kelly based strategies versus the constant leverage models. The best Kelly based money management strategy in terms of the DAG metric is the one with the parameter combination ($I = USSP2, c = 1.00$) with a DAG value of 0.2968 and a corresponding Sharpe ratio of 1.18. In contrast, the best constantly leveraged FX carry portfolio is the model with a constant leverage level of 1.5. This portfolio exhibited a DAG value of 0.0726 and a Sharpe ratio of 0.64.

The results summarised in Table 6.1 also illustrate the high level of risk associated to the full Kelly strategy with the non-informative confidence measure (i.e. $I = NAIVE$ and $c = 1.00$). The high maximum drawdown of 94.01% is responsible for a very low DAG value of 0.0143. Thus, despite the decent Sharpe ratio of 0.72, we would not recommend this type of strategy in multi period investment situations. Similar results are generated by the full Kelly strategy with the confidence measure based on the CBOE S&P 500 Volatility Index (i.e. $c = 1.00$ and

$I = VIX$). While the strategy generates a good Sharpe ratio of 0.75 and a high capital growth of 23.60% per annum, the high maximum drawdown of 76.62% and the low DAG value of 0.0628 indicate the excessive risk inherent to the full Kelly strategy with $I = VIX$. As the risk appetite factor c assumes lower values, the risk-adjusted performance metrics of these strategies improve. We observe that the most profitable strategies assume their maximum DAG value at higher values of c than the more volatile and less profitable strategies. Since future strategy performances are not known, we would suggest to set the risk appetite coefficient at a conservative level (i.e., $c < 1$).

Overall, weighting the expected return estimate $\hat{\mu}$ with confidence measures based on risk factors enhances the risk-adjusted performance metrics of the time-varying leverage strategies. For all levels of risk appetite c, the Kelly strategies weighted with confidence measures based on risk factors ($I=USSP2$, $TEDSP$, VIX, AVG) outperform the non-informative confidence measure ($I = NAIVE$) in terms of drawdown-adjusted-growth DAG and Sharpe ratio SR. As far as the suitability of specific risk factors as confidence measures for FX carry portfolios is concerned, we find that the best results were generated by the 2-Year U.S. Swap Spread risk factor ($USSP2$). The average confidence measure (AVG) produced good and robust results (only second to $I = USSP2$ in therms of the Sharpe ratio SR).

Leverage	Parameter	f_{AVG}	r^g	MAX.DD	DAG	SR
Constant	1.0	1.00	0.0589	0.2983	0.0712	0.64
Constant	1.5	1.50	0.0845	0.4234	0.0726	0.64
Constant	5.5	5.50	0.1854	0.9332	0.0128	0.64
Time-varying	I=NAIVE,c=1.00	7.50	0.2315	0.9401	0.0143	0.72
Time-varying	I=USSP2,c=1.00	4.49	0.3830	0.4608	0.2968	1.18
Time-varying	I=TEDSP,c=1.00	4.09	0.2503	0.4381	0.2066	0.89
Time-varying	I=VIX,c=1.00	5.09	0.2360	0.7662	0.0628	0.75
Time-varying	I=AVG,c=1.00	4.56	0.3073	0.5422	0.1881	1.00
Time-varying	I=NAIVE,c=0.50	3.75	0.1753	0.6680	0.0707	0.72
Time-varying	I=USSP2,c=0.50	2.25	0.2109	0.2464	0.2954	1.18
Time-varying	I=TEDSP,c=0.50	2.05	0.1415	0.2339	0.2055	0.89
Time-varying	I=VIX,c=0.50	2.54	0.1483	0.4824	0.1081	0.75
Time-varying	I=AVG,c=0.50	2.28	0.1729	0.3092	0.2029	1.00
Time-varying	I=NAIVE,c=0.25	1.88	0.1011	0.3883	0.0956	0.72
Time-varying	I=USSP2,c=0.25	1.12	0.1102	0.1271	0.2272	1.18
Time-varying	I=TEDSP,c=0.25	1.02	0.0747	0.1206	0.1580	0.89
Time-varying	I=VIX,c=0.25	1.27	0.0813	0.2700	0.1065	0.75
Time-varying	I=AVG,c=0.25	1.14	0.0911	0.1648	0.1643	1.00

Table 6.1: Performance Metrics of Constant and Time-varying Leverage Models for FX Carry Portfolio Money Management (f_{AVG}: Average Leverage Level, r^g: Annualized Geometric Return, $MAX.DD$=Maximum Drawdown, DAG: Drawdown-Adjusted-Growth Measure, SR: Sharpe Ratio)

PANEL A
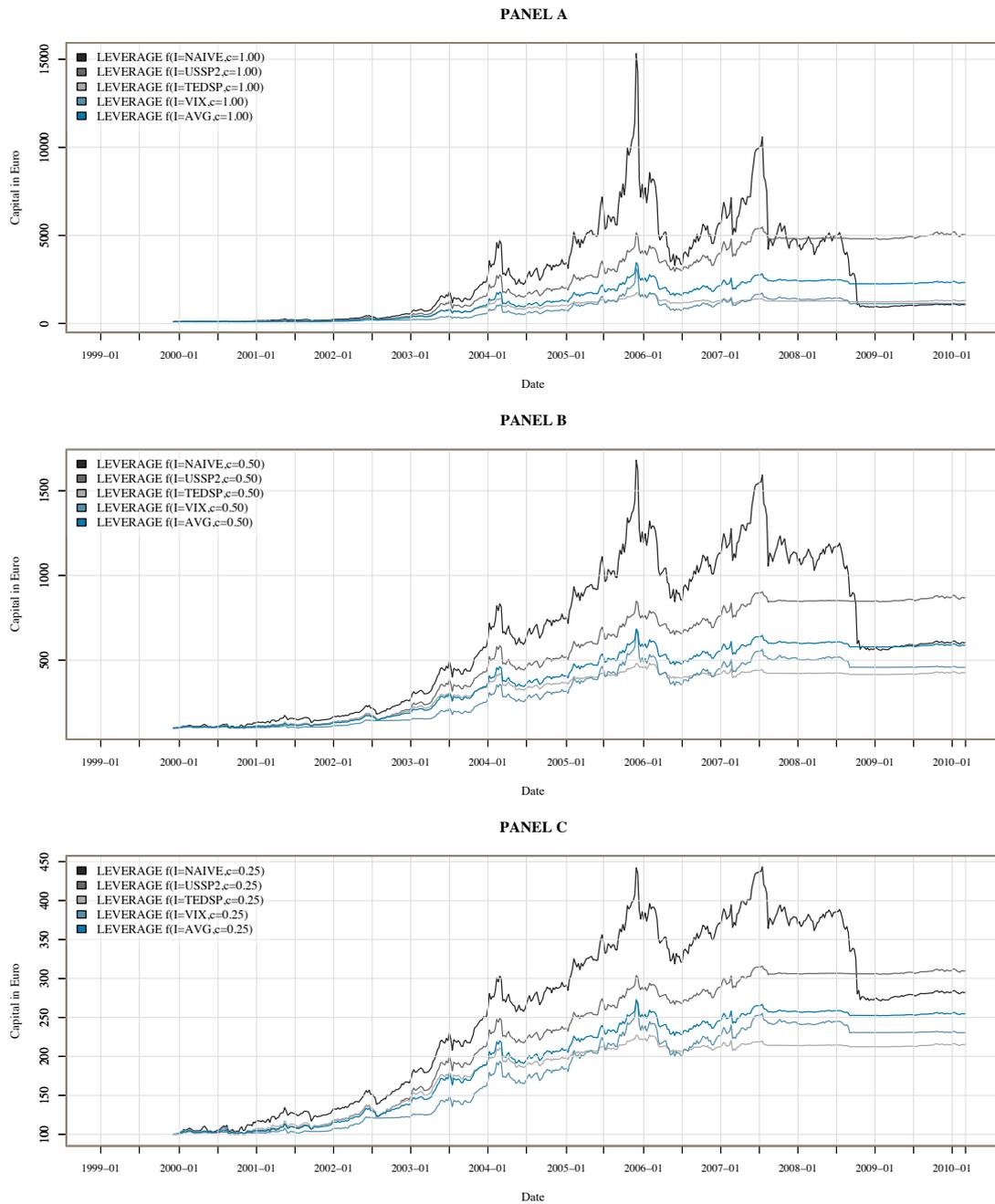
PANEL B

PANEL C

Figure 6.4: Capital Growth of 100 EUR for FX Carry Portfolios with Time-varying Leverage Levels computed according to $f_t^*(I,c) = \frac{\hat{\mu}_t \kappa_{I,t}}{\hat{\sigma}_t^2} c$ with the Parameters $I = NAIVE, USSP2, TEDSP, VIX, AVG$ and $c = 1.00$ (PANEL A); $c = 0.50$ (PANEL B); $c = 0.25$ (PANEL C)

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The results of the regressions for *carry-alpha* and market-timing ability of the money management models are summarised in Table 6.2 and Table 6.3.

The constantly leveraged FX carry portfolios by construction exhibit no *carry-alpha*, and a *carry-beta* equal to the constant leverage level inherent to the specific portfolio (see Table 6.2 and Table 6.3). Similarly, the Kelly-based money management strategies, exhibit α and β coefficients which increase proportionally to the value of the risk appetite factor c. All Kelly strategies exhibit positive *beta* coefficients, with the Kelly strategy weighted by the non-informative confidence measure ($I = NAIVE$) displaying the highest *beta* estimates (respectively 1.26, 2.51 and 5.02 for settings of c of 0.25, 0.50 and 1.00).

The Kelly strategies with confidence measures based on the risk factors $USSP2$, $TEDSP$ and AVG exhibit a statistically significant positive α coefficient at a significance level of 5%. Also the Kelly strategies weighted with the confidence measures $NAIVE$ and VIX exhibit a positive *alpha* coefficient, albeit not at a statistically significant level.

By examining the results in Table 6.3, we find that these statistically significant positive *carry-alpha* coefficients disappear when the regressions are extended with a market-timing term γF_t^2. The *carry-alpha* produced by the Kelly-based money management strategies is now captured by the market-timing coefficient γ, which is now statistically significantly positive for Kelly strategies with the confidence measures $I = USSP2, TEDSP, VIX, AVG$. The non-informative confidence measure ($I = NAIVE$) retains a relatively high *alpha* value, albeit not statistically significant, while being the only one that exhibits a negative market-timing term (also at a non significant level).

6.6   Conclusion

In this chapter, we examined the effect of various money management strategies on the equity of FX carry portfolios.

In a first step, we tested the performance of trading the *Benchmark FX Carry Portfolio* (see Appendix A) with constant leverage levels ranging from 0.5 to 10. During the analysed data period, we find that a constant leverage level of 5.5 would have produced the highest capital growth, while a constant leverage level of 1.5 would have been optimal according to the risk-adjusted performance criterion DAG (see Section 6.5.1). Still, we would not advocate to select the leverage level for FX carry trades according to this methodology. Firstly, the leverage

Leverage	Parameter	α	$Pr(>|t_\alpha|)$	β	$Pr(>|t_\beta|)$
Constant	1.0	-0.0000	1.00	1.00	0.00
Constant	1.5	0.0000	0.56	1.50	0.00
Constant	5.0	0.0000	0.01	5.50	0.00
Time-varying	I=NAIVE,c=1.00	0.0026	0.28	5.02	0.00
Time-varying	I=USSP2,c=1.00	0.0061	0.00	2.22	0.00
Time-varying	I=TEDSP,c=1.00	0.0036	0.04	2.01	0.00
Time-varying	I=VIX,c=1.00	0.0036	0.13	2.63	0.00
Time-varying	I=AVG,c=1.00	0.0046	0.01	2.29	0.00
Time-varying	I=NAIVE,c=0.50	0.0013	0.28	2.51	0.00
Time-varying	I=USSP2,c=0.50	0.0031	0.00	1.11	0.00
Time-varying	I=TEDSP,c=0.50	0.0018	0.04	1.00	0.00
Time-varying	I=VIX,c=0.50	0.0018	0.13	1.32	0.00
Time-varying	I=AVG,c=0.50	0.0023	0.01	1.14	0.00
Time-varying	I=NAIVE,c=0.25	0.0006	0.28	1.26	0.00
Time-varying	I=USSP2,c=0.25	0.0015	0.00	0.56	0.00
Time-varying	I=TEDSP,c=0.25	0.0009	0.04	0.50	0.00
Time-varying	I=VIX,c=0.25	0.0009	0.13	0.66	0.00
Time-varying	I=AVG,c=0.25	0.0011	0.01	0.57	0.00

Table 6.2: Regression Results for the Factor Model $R_t = \alpha + \beta F_t + \epsilon_t$ ($F_t = $ Benchmark FX Carry Portfolio Returns, $R_t = $ Money Managed Carry Portfolio Returns).

Leverage	Parameter	α	$Pr(>|t_\alpha|)$	β	$Pr(>|t_\beta|)$	γ	$Pr(>|t_\gamma|)$
Constant	1.0	-0.0000	1.00	1.00	0.00	0.00	0.37
Constant	1.5	0.0000	0.58	1.50	0.00	-0.00	0.62
Constant	5.5	0.0000	0.01	5.50	0.00	-0.00	0.10
Time-varying	I=NAIVE,c=1.00	0.0039	0.12	4.92	0.00	-6.28	0.13
Time-varying	I=USSP2,c=1.00	0.0030	0.14	2.46	0.00	14.84	0.00
Time-varying	I=TEDSP,c=1.00	0.0009	0.63	2.21	0.00	12.70	0.00
Time-varying	I=VIX,c=1.00	-0.0000	0.99	2.91	0.00	16.98	0.00
Time-varying	I=AVG,c=1.00	0.0014	0.46	2.53	0.00	14.81	0.00
Time-varying	I=NAIVE,c=0.50	0.0020	0.12	2.46	0.00	-3.14	0.13
Time-varying	I=USSP2,c=0.50	0.0015	0.14	1.23	0.00	7.42	0.00
Time-varying	I=TEDSP,c=0.50	0.0004	0.63	1.11	0.00	6.35	0.00
Time-varying	I=VIX,c=0.50	-0.0000	0.99	1.46	0.00	8.49	0.00
Time-varying	I=AVG,c=0.50	0.0007	0.46	1.26	0.00	7.40	0.00
Time-varying	I=NAIVE,c=0.25	0.0010	0.12	1.23	0.00	-1.57	0.13
Time-varying	I=USSP2,c=0.25	0.0007	0.14	0.62	0.00	3.71	0.00
Time-varying	I=TEDSP,c=0.25	0.0002	0.63	0.55	0.00	3.17	0.00
Time-varying	I=VIX,c=0.25	-0.0000	0.99	0.73	0.00	4.25	0.00
Time-varying	I=AVG,c=0.25	0.0004	0.46	0.63	0.00	3.70	0.00

Table 6.3: Regression Results for the Factor Model $R_t = \alpha + \beta F_t + \gamma F_t^2 + \epsilon_t$ ($F_t = $ Benchmark FX Carry Portfolio Returns, $R_t = $ Money Managed Carry Portfolio Returns).

levels of 5.5 and 1.5 are selected with hindsight after having analysed the performance of 20 different leverage levels. Secondly, the drawdowns associated with these historically optimal constant leverage levels are very large (42.34% with a leverage of 1.5 and 93.32% with a leverage of 5.5). In addition, Figure 6.2 provides an intuitive visualisation of how a historical optimisation of leverage levels could have drawn an investor to select an excessive leverage level in the period

preceding the credit crisis: Before the credit crisis, the maximum growth level would have been generated at a leverage level far above 10 (the maximum growth would be located in a leverage region outside the margins of Figure 6.2). Thus a reliance on the historically optimal constant leverage level would have caused highly leveraged speculators to go bankrupt during the large FX carry trade drawdown inherent to the credit crisis. By referring to an interview with an FX hedge fund manager held in April 2009 (see Appendix C), we posit that some FX hedge funds may have committed the mistake of optimising their leverage levels for the FX carry trade historically, and thus were forced to liquidate after having incurred amplified drawdowns during the credit crisis.

In our second empirical analyses in this chapter we focused on the performance of time-varying leverage models based on the Kelly criterion. Notorious weaknesses of the Kelly criterion for determining optimal leverage levels are

- the high short-term risk associated with the Kelly strategy, and

- the danger of overleveraging due to erroneous estimation of the input parameters return $\hat{\mu}$ and variance $\hat{\sigma^2}$ (see Section 6.1.3).

In Section 6.4.2 we suggested extensions to the Kelly formula that address these issues. We computed and tested various time-varying leverage levels based on different parameters for the extended Kelly formula. Our results suggest that applying the time-varying leverage model produces enhanced results over the constant leverage models in terms of geometric return and drawdown-adjusted geometric return (see Section 6.5.2). The risk-adjusted performances of the worst time-varying leverage models improve, as the risk appetite factor c assumes lower values (see Section 6.4.2). Thus, we confirm the validity of the heuristic proposed by e.g., Thorp [2006] and Ziemba [2003] of reducing risk by trading fractions of the Kelly position size.

Weighting the estimate of the return to the FX carry portfolio by confidence measures derived from risk factors (see Section 6.4.3) also contributes to improve the performance of the carry portfolios. Similarly to the market-timing study in Chapter 5, we find that the 2-Year U.S. Swap Spread ($USSP2$) based indicator generated the best FX carry trading performance during the period of interest. The confidence measure based on the average of the single confidence measures (AVG), produced second best results across all levels of risk appetite c. Thus, we

confirm that aggregating individual risk factors for trading FX carry portfolios generates stable results (see Chapter 5).

In the regressions for *carry-alpha* and market-timing ability summarised in Table 6.2 and Table 6.3, we find explanations for the improved performance of weighting the estimated FX carry portfolio return $\hat{\mu}$ with a confidence measure based on risk factors: The statistically significant positive *alpha* for the strategies weighted with the confidence measures with $I = USSP2, TEDSP, AVG$ disappears as we extend the form of the equation to include a market-timing term (see Equation 5.2). In contrast, the market-timing coefficient γ becomes statistically significantly positive for $I = USSP2, TEDSP, VIX, AVG$. Thus, a flexible money management methodology has the ability to address both the aspect of optimal position sizing and market-timing through variation of the leverage levels. Pojarliev and Levich [2008] showed that some FX hedge funds exhibit positive market-timing ability by performing regressions of the form of Equation 5.2. Our results do not exclude that these money managers might instead adopt time-varying leverage techniques, similar to the one proposed in Section 6.4.2. Money managers who rely on simple market-timing techniques without considering leverage are not trading optimally with respect to multi-period (risk adjusted) capital growth.

Finally, our analyses on dynamic leverage models for FX carry portfolios strongly questions the validity of the conclusions reached by Darvas [2009]. Darvas [2009] finds that the Sharpe ratio of FX carry trades degenerates with increasing leverage levels. Thus, following Darvas [2009], the UIP puzzle would exist mostly in the data and FX traders can not capitalise on it because of their high leverage. Firstly, while Galati et al. [2007b] state that FX carry trades are executed with leverage, there is no evidence whether these leverage levels are particularly high or just moderate. Secondly, as we show in our analyses, the Sharpe ratio proves to be not appropriate for measuring risk adjusted capital growth. Thus, we postulate that the conclusions reached by Darvas [2009] is drawn upon wrong assumptions and interpretations of results.

Moreover, we show how optimising leverage levels based on historical returns series can lead to strong overleveraging, and consequently to bancrupcy. Dynamic, conditional optimal leverage models are more reactive and as Thorp [2006] points out, theoretically sound. Our results, show how most of the conditional leverage models could outperform the constant leverage models with respect to

our novel performance measure (DAG).

Chapter 7

Conclusion

In this thesis we analysed the return characteristics inherent to advanced FX carry trade strategies. The FX carry trade is of major practical relevance since it represents a significant investment-style implemented by professional FX managers (see Pojarliev and Levich [2008]). Pojarliev and Levich [2008] argued that FX managers should not be remunerated for naive replication of FX carry returns since the returns inherent to the FX carry trade can be generated in an easy and systematic manner. As a solution Pojarliev and Levich [2008] suggested that FX managers performance should be assessed according to new benchmarks which entail proxies to the major investment-styles for the FX market. An industry-wide acceptance of such benchmarks would force professional FX managers to develop new trading strategies or to enhance existing ones (see Section 3.1).

The FX carry trade is relevant also from the theoretical perspective of financial economics, since its profitability stems from the well documented empirical failure of uncovered interest rate parity (see Section 3.2). Since the FX carry trade has been identified as a main driver of increases in FX market turnover (see Galati and Melvin [2004]), an acknowledgement of the carry trade phenomenon is indispensable for understanding current FX market dynamics. Throughout the thesis we discussed literature which analysed various aspects of the FX carry Trade phenomenon. Among others, Rosenberg [2003] and Vesilind [2006] studied the performance of FX carry portfolios and reported the existence of diversification benefits when implementing FX carry trades. Hochradl and Wagner [2010] simulated the returns to a carry portfolio strategy and conclude that the risk adjusted returns to carry trading are too high to be ignored by professional speculators. Christiansen et al. [2009] and Menkhoff et al. [2009] analysed which risk

factors contribute in explaining the returns inherent to the carry trade and found significant negative relationships between changes in proxies for global volatility and liquidity and carry trade returns. Dunis and Miao [2007] deployed volatility-based filters for market-timing the FX carry trade and finds improved Sharpe ratios over a long-only carry trade benchmark. Darvas [2009] analysed the effect of constant leverage levels on carry trade performance and finds that risk-adjusted carry trading performances deteriorate as the leverage levels increase.

In the following we will briefly summarise the main findings from our three empirical chapters.

Asset Allocation   Since carry trading involves buying high yielding currencies while selling low yielding currencies, an FX carry trade should involve a minimum amount of two currencies. The maximum number of currencies in a FX carry portfolio however, is not limited. Rosenberg [2003] and Vesilind [2006] showed that diversified FX carry portfolios generated higher risk-adjusted returns than FX carry trades involving only two currencies. By analysing the performance of three different sets of currency portfolios, in Chapter 4 we contribute to literature analysing the effect of asset allocation methodologies on FX carry trade profitability.

Within the first set of currency portfolios we implement different algorithms for computing the portfolio weights of diversified FX carry trade portfolios. We find that diversification improves the Sharpe ratio of FX carry portfolios and thereby confirm the validity of the findings by Rosenberg [2003] and Vesilind [2006] in our own empirical results. Moreover, we find that mean-variance asset allocation strategies exhibit better financial performance metrics than the simple asset allocation strategies. Nevertheless, mean-variance asset allocation strategies fail to significantly outperform a simple scorecard-based asset allocation methodology. Also, we attribute a higher robustness to the simple asset allocation algorithms, since they do not require an additional estimation of the variance-covariance matrix. Thus, we do not regard mean-variance optimisation as the better asset allocation procedure for FX carry portfolios and concentrate our research efforts on a simple *Benchmark FX Carry Portfolio*, diversified according to a simple scorecard-based weighting scheme (see Appendix A).

Secondly, we test alternative FX carry portfolios by establishing currency exposures based on different yield maturities. We find that the best performances were achieved by ranking the currencies according to the yields with the shortest maturity (i.e. 1-week yields). Nevertheless, the utilisation of longer maturity yields does not significantly underperform portfolios based on shorter yield durations.

The third set of currency portfolios tested in Chapter 4 establish currency positions according to relative changes in measures of carry trade attractiveness. These currency portfolios mimic the portfolio flows generated by carry traders in the FX market.

Contrary to the first two sets of currency portfolios, we find that these 'carry-flows' portfolios generate stable positive returns from the FX rate component while generating no exceptional return from the yield component. We posit that these positive FX returns are due to sustained buying (selling) pressure of FX traders on currencies which are gaining (losing) carry trade attractiveness.

Although the *carry-flows* currency portfolios generate high returns from FX fluctuations, the total returns to the portfolios are relatively low, since high transactions costs erode large parts of the profits generated by the strategies. Following Lyons [2006] and Sarno et al. [2006], the low Sharpe ratios associated to the *carry-flows* portfolios should not attract significant speculative capital. Thus, according to the limits of speculation hypothesis (see Section 4.1) the positive FX rate returns inherent to *carry-flows* strategies could persist in the future. Nevertheless, we posit that *carry-flows* portfolio strategies constitute a good diversification vehicle for FX carry portfolios, since they exhibit positive returns and consistently negative correlations to the *Benchmark FX Carry Portfolio*.

Market Timing Pojarliev and Levich [2008] found that about half of the examined FX hedge funds successfully perform market-timing in one or more investment-styles (see Section 5.1.2). In order to gain some insights into the strategies adopted by modern FX hedge funds and contribute to literature relating FX carry trade returns to global risk factors, in Chapter 5 we analysed the performance of market-timing the *Benchmark FX Carry Portfolio* through market-timing signals based on various risk factors.

We constructed simple market-timing signals based on proxies for global liq-

uidity, volatility and interest rate differentials. We find that while long-neutral market-timing strategies could outperform the long-only FX carry trade benchmark, long-short market-timing strategies consistently underperformed the long only FX carry benchmark. On the basis of these results, we would not recommend assuming short positions in the carry trade. Moreover, we find that the best trading performances were achieved by the market-timing signals based on proxies for global liquidity (i.e. the Ted Spread and the U.S. 2-Year Swap Spread). Composed risk aversion indicators, as disseminated by several financial institutions, produced stable trading performances which were comparable to the performances of the best single indicators.

By fixing the threshold parameter for the generation of the market-timing signals to 0.7 from the start, we avoided allowing our analysis to degenerate into a data-mining exercise. Still, we find our results affected by a lookback bias: The enhanced profitability of the market-timed carry trade strategies is grounded in the successful timing of the credit crisis. We strongly question whether carry traders would have chosen the right (liquidity-based) risk indicators for timing the carry trade before the credit crisis.

Since we do not know ex-ante which risk indicator will perform well within future periods of carry trade losses, we advocate careful consideration of both positive and negative market scenarios when developing market-timing indicators. For practical market-timing applications, we would advocate the use of aggregated risk indicators, which have been shown to produce robust trading results.

Money Management   FX carry trades are typically executed with leverage (see Gagnon and Chaboud [2007] and Galati et al. [2007b]). In a recent publication, Darvas [2009] analysed the effect of leverage on the profitability of FX carry trades. Darvas [2009] found that risk-adjusted trading performances of FX carry strategies decrease as leverage levels rise. This finding led Darvas [2009] to conclude that FX markets might be more speculative efficient than previously reported, since leveraged FX carry traders generated worse trading results than unleveraged FX carry strategies which are typically analysed in the carry trade literature.

In Chapter 6 we examine the effect that leverage has on FX carry trades

by replicating and extending the research initiated by Darvas [2009]. In the theoretical part of Chapter 6 (see Section 6.1) we discuss the implications of using the Kelly criterion for determining optimal leverage levels. In Section 6.4 we propose a novel performance metric (Drawdown-adjusted-Growth DAG) which permits the evaluation of trading strategies with respect to capital growth and security. We posit that the DAG is more appropriate for assessing multi period investment performance than standard risk-adjusted performance measures like the Sharpe ratio. Moreover, we propose extensions to the Kelly formula for determining optimal leverage levels.

In the first part of our empirical analysis on leveraged FX carry trades we simulate the trading performance of FX carry portfolios executed with different fixed leverage factors. We find that when trading the *Benchmark FX Carry Portfolio* (see Appendix A), a leverage level of 5.5 would have produced the highest capital growth, while a leverage level of 1.5 would have produced the highest risk-adjusted capital growth (as measured by the DAG).

Moreover, we show that carry traders who determined their leverage level by selecting the historically growth-optimal constant leverage level would have found themselves overleveraged during the period of the credit crisis. As a result, their portfolios would have incurred substantial losses.

In the second part of the empirical research in Chapter 6 we analyse the performance of trading the *Benchmark FX Carry Portfolio* with a time-varying leverage model based on the Kelly criterion. We find that the time-varying leverage models perform better than the optimised constant leverage levels, which were selected with hindsight on their performance.

Our trading experiments in Chapter 6 document the large effects that leverage has on the capital growth and the drawdowns of FX carry trade portfolios. We posit that the large and sudden unwinding of carry trade positions during drawdown phases, might be the result of forced liquidations of positions by over-leveraged carry traders.

Outlook   To recapitulate, in this thesis we focused on analysing the popular FX carry trade. Reviewing recent carry trade literature, we showed that an acknowledgement of the practical relevance of the FX carry trade is important for an improved understanding of current FX market dynamics. We also conclude that modern FX managers will have to develop enhanced methodologies for implementing FX carry trades in order to compete with low cost index products

which replicate popular investment-styles like the FX carry trade. In addition, we find that there might be a feedback effect between the failure of uncovered interest rate parity and the trading activity of FX carry traders.

Further, through the empirical analyses performed within the thesis, we showed that:

- Diversification is beneficial to FX carry portfolio performance;

- Mean-variance optimisation does not significantly outperform the benchmark FX carry strategies;

- The FX market offers pockets of predictability facilitated by sustained buying and selling pressure on specific currencies by FX carry traders;

- Long-neutral market-timing can deliver improved risk-adjusted FX carry performances, while long-short market-timing generates considerably lower trading performances;

- Robust, aggregated market-timing indicators should be preferred to historically optimal indicators, in order to avoid overoptimisation and a lookback-bias;

- Historical optimisation of leverage levels bears risks of overleveraging and low flexibility to adapt in volatile market environments;

- Time-varying leverage levels based on Kelly produce enhanced results over constant leverage levels;

- Performance measurement for multi-period trading strategies where leverage is allowed, is achieved better by the DAG (see Section 6.4.4) than by conventional risk-adjusted performance metrics like e.g., the Sharpe ratio.

An interview with a FX hedge fund manager held in April 2009, following the major FX carry trade losses incurred during the period of the credit crisis (see Appendix C), provides a confirmation on the wide implementation of FX carry strategies by FX hedge funds; the ability of some FX managers to market-time the FX carry trade; and the failure of some FX managers to adopt effective money- and risk management procedures. We stress the importance of this point, since some FX hedge funds were forced to liquidate following the large losses incurred

during the credit crisis.

We conclude that since the determination of the leverage levels for FX carry trades constitutes the major factor in the final performance of FX carry trade strategies, professional FX managers should put a greater focus on implementing money management techniques for determining optimal leverage levels. Further work in this area should focus on the optimal computation of the inputs to the Kelly formula and on the development of solutions to the Kelly criterion for return distributions which model the negative skewness and leptokurtosis inherent to FX carry trade returns in a better way than the normal distribution.

Also, we stress the relevance of the findings that FX carry trade portfolio flows can signal pockets of predictability in the movements of G10 exchange rates. Further work in this area should deal with a refinement of a measure for determining the change in FX carry trade attractiveness, the analysis of diversification benefits gained by the inclusion of *carry-flows* portfolios in an FX carry portfolio, and the interdependence of returns to the FX carry trade and *carry-flows* portfolios.

Appendix A

The Benchmark FX Carry Portfolio

In the following the we will outline the backtesting procedure and performance metrics for the carry portfolio used as the simple proxy for carry trade returns throughout this thesis. The computation of all currency portfolios in the thesis is performed according to the methodology outlined in the following sections.

A.1   Defining the Currency Universe

The currency universe for the benchmark carry portfolio is denoted by the G10 currencies, i.e. the EUR, USD, JPY, GBP, CHF, CAD, AUD, NZD, NOK, SEK (see Section 2.2).

A.2   Computing the Portfolio Weights

The portfolio weights for the benchmark carry portfolio are computed according to the simple scorecard-based approach outlined in Section 4.4.1. Equally weighted long positions are established with the three highest yielding currencies and equally weighted short positions are established with the three lowest yielding currencies. Figure A.1 depicts the resulting cumulative portfolio weights from the 1st of January 1999 to the 5th of March 2010 of the *Benchmark FX Carry Portfolio*.
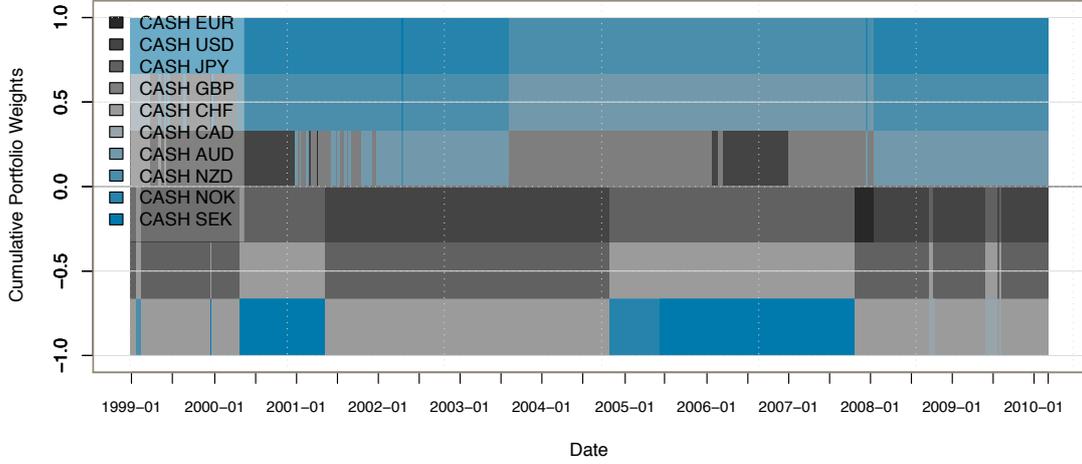
Figure A.1: Cumulative Portfolio Weights of the Benchmark FX Carry Portfolio

A.3 Simulating the Returns

The total returns to the currency portfolios are composed of three components. These components are the return from FX rate movements, the return from yield differentials and the transactions costs.

The FX return component $r_{FX,t}^P$ of a currency portfolio is calculated via Equation A.1:

$$r_{FX,t}^P = \sum_{c=1}^{10} w_{t-1}^c * log(\frac{S_t^c}{S_{t-1}^c}) \tag{A.1}$$

Where c denotes the identifier for a specific currency in the $G10$ universe (see Section A.1), w_{t-1}^c denotes the portfolio weight for currency c in period $t-1$ and $log(\frac{S_t^c}{S_{t-1}^c})$ denotes the percentage change of the exchange rate of currency c to the Euro EUR from period $t-1$ to period t.

The yields return component $r_{YD,t}^P$ of the currency portfolio is calculated via Equation A.2:

$$r_{YD,t}^P = \sum_{i=1}^{10} w_{t-1}^c * (\frac{i_{t-1}^c}{52} + sign(w_{t-1}^c) * \frac{\eta}{2}) \tag{A.2}$$

Where i_{t-1}^c denotes the 1-week interest rate for currency c in period $t-1$ and η denotes the bid-ask spread for the 1-week yields. In order to determine the

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yield pickup for our weekly holding period, we divide the 1-week yields by 52 (the number of weeks in one year). Throughout the thesis we set the value of η to 0.05% (i.e. 5 basis points) for all $G10$ currencies.

The transactions costs component $r^P_{TC,t}$ of the currency portfolio is calculated via Equation A.2:

$$r^P_{TC,t} = \sum_{i=1}^{10} -|w^c_t - w^c_{t-1}| * (\kappa + \zeta) \tag{A.3}$$

Where κ denotes the transactions costs in percent for a one-way foreign exchange transaction and ζ denotes the slippage in percent for a one-way foreign exchange transaction. We set κ to 0.03% and ζ to 0.02% throughout the thesis.

Thus, the total return $r^P_{TOT,t}$ generated by a currency portfolio P in a specific period t can be computed via Equation A.4:

$$r^P_{TOT,t} = r^P_{FX,t} + r^P_{YD,t} + r^P_{TC,t} \tag{A.4}$$

The PANEL A of Figure A.2 depicts the cumulative total returns inherent to the *Benchmark FX Carry Portfolio* as well as the cumulative single returns components discussed above (i.e. FX, yields and transactions costs). The PANEL A of Figure A.2 visualises how the largest contribution to the total returns of the *Benchmark FX Carry Portfolio* is given by the yield component. The PANEL B of Figure A.2 depicts the histogram of the *Benchmark FX Carry Portfolio* total returns. The histogram visualises the existence of a few large (negative) outliers in the total returns of the *Benchmark FX Carry Portfolio*. An analysis of the cumulative returns depicted in PANEL A of Figure A.2 reveals that, within our data set, the *Benchmark FX Carry Portfolio* incurred its largest drawdown during the period of the credit crisis.

A.4 Performance Analysis

The performance metrics for the *Benchmark FX Carry Portfolio* are summarised in Table A.1. The computation of these performance measures is outlined in Appendix B.

The portfolio generated a return of 6.51% *per annum* with a standard deviation of the returns of 9.71%. This yields a Sharpe ratio of 0.67. The maximum drawdown of the *Benchmark FX Carry Portfolio* was 30%.
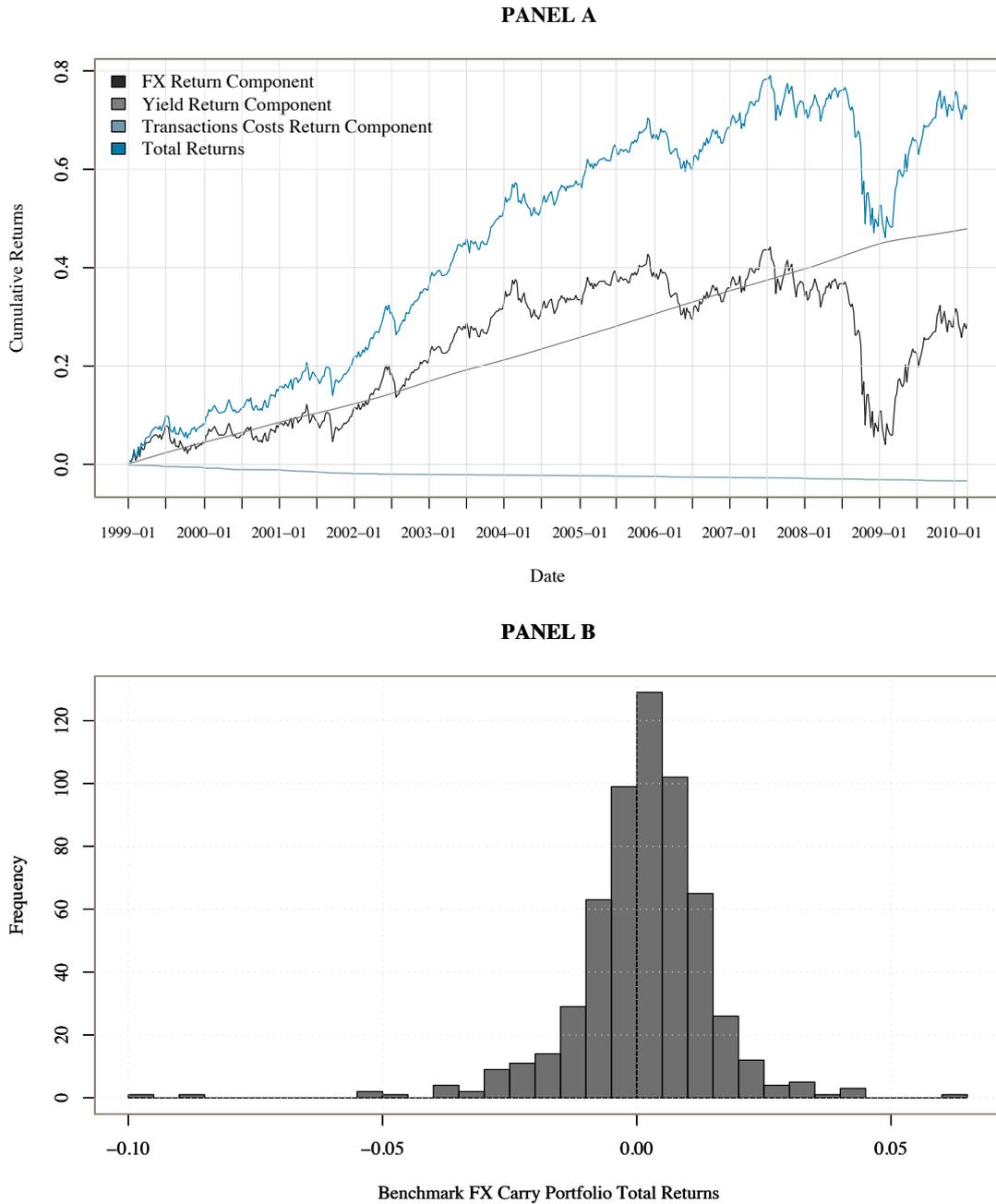
Figure A.2: PANEL A: Cumulative Returns of the Benchmark FX Carry Portfolio. PANEL B: Returns Histogram of the Benchmark FX Carry Portfolio

r^a	σ^a	SR	r^g	$MAX.DD$	DAG
0.0651	0.0971	0.67	0.0604	0.30	0.0727

Table A.1: Performance Metrics for the Benchmark FX Carry Portfolio (r^a: Annualised Arithmetic Return, σ^a: Annualised Standard Deviation of Returns, SR: Sharpe Ratio, r^g: Annualised Geometric Return, $MAX.DD$: Maximum Drawdown, DAG: Drawdown Adjusted Growth)

A.5 Timeseries derived from the Benchmark FX Carry Portfolio

The yield differentials (*carry*) and the *RiskMetrics* volatility inherent to the *Benchmark FX Carry Portfolio* are used as risk indicators in Chapter 5 and Chapter 6 of the thesis. The computation of these time series is outlined in the following paragraphs.

Benchmark FX Carry Portfolio 'Carry' We compute the time series of interest rate differentials (*carry*) inherent to the *Benchmark FX Carry Portfolio* according to Equation A.5:

$$C_t^{BMCP} = \sum_{i=1}^{10} w_t^c * i_t^c \tag{A.5}$$

Where C_t^{BMCP} denotes the actual yield differential inherent to the *Benchmark FX Carry Portfolio* positions, w_t^c denotes the current portfolio weight of currency c in the carry portfolio and i_t^c denotes the current 1-week interest rate for currency c. We compute the *yield differentials* for all periods of our weekly data set ranging from the 1st of January 1999 to the 5th of March 2010.

Benchmark FX Carry Portfolio *RiskMetrics*-Volatility In order to compute the time series of *RiskMetrics* volatility inherent to the *Benchmark FX Carry Portfolio*, we need to calculate the portfolio weights $\mathbf{w}^{BMCP}$ of the *Benchmark FX Carry Portfolio* as well as the *RiskMetrics* variance-covariance matrix $\mathbf{\Sigma}_{rr}$ for the $G10$ currencies. The calculation of the portfolio weights is outlined in Section A.2 while the methodology for the calculation of the *RiskMetrics* variance-covariance matrix is outlined in Section 4.4.3. After having computed these two inputs we can compute the time series of *RiskMetrics* volatility inherent to the *Benchmark FX Carry Portfolio* according to Equation A.6:

$$V_t^{BMCP} = \sqrt{52 * \mathbf{w}_t^{BMCP\prime} * \mathbf{\Sigma}_{rr,t} * \mathbf{w}_t^{BMCP}} \tag{A.6}$$

Where V_t^{BMCP} denotes the actual *RiskMetrics*-volatility inherent to the *Benchmark FX Carry Portfolio*, $\mathbf{w}_t^{BMCP}$ denotes the (10×1) vector of weights of the *Benchmark FX Carry Portfolio* in period t and $\mathbf{\Sigma}_{rr,t}$ denotes the (10×10) *RiskMetrics* variance-covariance matrix of the $G10$ currencies in period t. The standard deviation measure is annualised through multiplication with the square root of 52 (number of weeks in one year).

Figure A.3 depicts the *Carry* and *RiskMetrics-Volatility* time series inherent to the *Benchmark FX Carry Portfolio*.

PANEL A
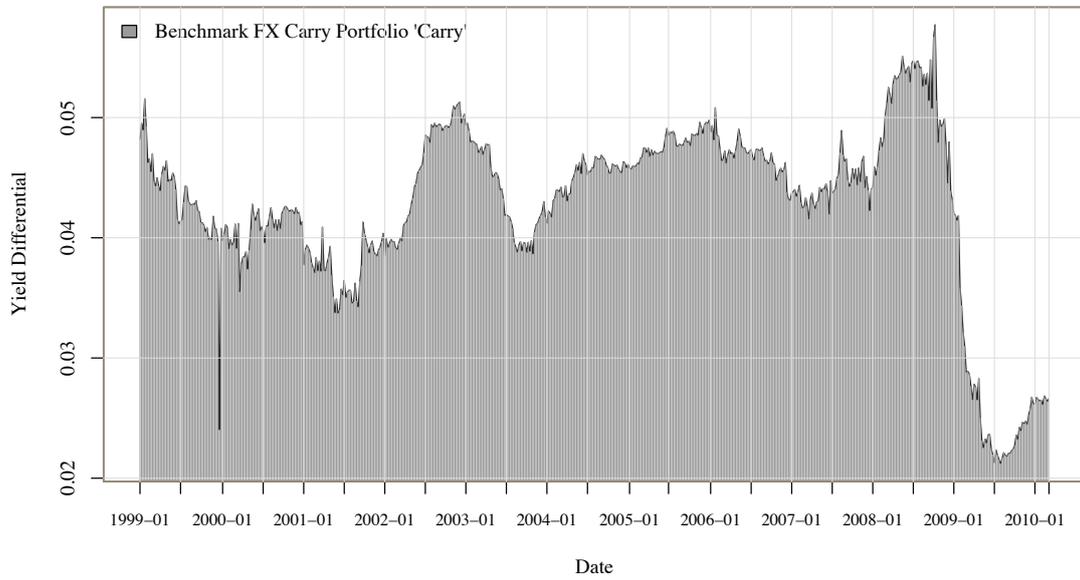
PANEL B
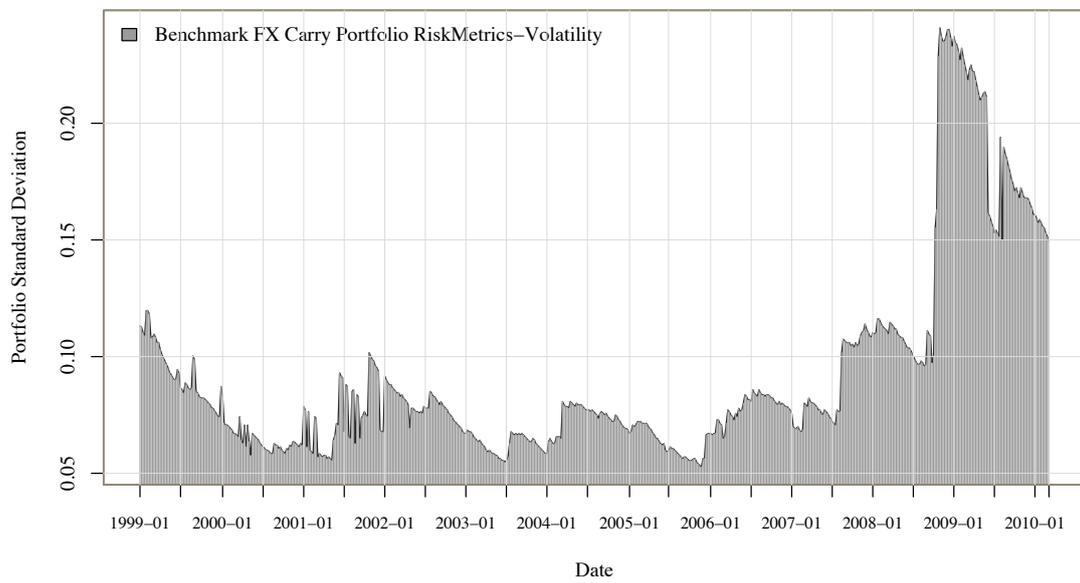
Figure A.3: Yield Differentials (PANEL A) and RiskMetrics Volatility (PANEL B) of the Benchmark FX Carry Portfolio

Appendix B

Performance Metrics

Throughout the thesis we utilise a set of performance metrics to evaluate the currency portfolios from a portfolio managers perspective. These performance metrics are:

- Annualised Arithmetic Return

- Annualised Standard Deviation

- Sharpe Ratio

- Annualised Geometric Return

- Maximum Drawdown

- Drawdown Adjusted Growth

In the following sections we will outline the computation of these performance metrics.

B.1 Annualised Arithmetic Return

We compute the arithmetic mean return for a trading strategy by calculating the average return for a period:

$$\hat{r} = \frac{1}{T} \sum_{t=1}^{T} r_{TOT,t}^{P} \tag{B.1}$$

Where $r_{TOT,t}^{P}$ denotes the total return generated by a currency portfolio P in a specific period t.

Since our currency portfolios are traded on a weekly basis, we annualise the mean return by multiplying it with the factor 52 (number of weeks in a year):

$$r^a = 52 * \hat{r} \tag{B.2}$$

B.2 Annualised Return Standard Deviation

We calculate the weekly standard deviation of returns via Equation B.3:

$$\hat{\sigma} = \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} (r_{TOT,t}^P - \hat{r})^2} \tag{B.3}$$

Subsequently we annualise the standard deviation by multiplying the weekly standard deviation by the factor $\sqrt{52}$:

$$\sigma^a = \sqrt{52} * \hat{\sigma} \tag{B.4}$$

B.3 Sharpe Ratio

The Sharpe ratio is a very popular risk-adjusted performance metric. We calculate the Sharpe ratio SR by dividing the strategy return over the riskfree rate $(r^a - r_{rf})$ by the annualised standard deviation of returns σ^a. We set the riskless interest rate r_{rf} in Equation B.5 to zero, since the currency portfolios are fully self financed.

$$SR = \frac{r^a - r_{rf}}{\sigma^a} \tag{B.5}$$

B.4 Annualised Geometric Return

When measuring the performance of an investment strategy over several periods the arithmetic mean return r^a, does not provide a realistic measure of investment performance since it does not take into account the compounding of returns over time. The geometric mean return r^g denotes the average return to a trading strategy under consideration of reinvestment of returns. The annualised geometric return is computed via Equation B.6:

$$r^g = 52 * \left(\prod_{t=1}^{T} (1 + r_{TOT,t}^P)^{\frac{1}{T}} - 1 \right) \tag{B.6}$$

B.5 Maximum Drawdown

The maximum drawdown metric $MAX.DD$ measures the biggest historical price decline in the equity of a trading strategy. If $X(t)$ is a random process $[X(0) = 0, t \geq 0]$, the drawdown $DD(T)$ at any time T is defined as:

$$DD(T) = Max[0, Max_{t \in (0,T)} X(t) - X(T)] \tag{B.7}$$

The maximum drawdown $MAX.DD$ up to time T is the maximum of the drawdown over the history of the variable. More formally,

$$MAX.DD(T) = Max_{\tau \in (0,T)}[Max_{t \in (0,\tau)} X(t) - X(\tau)] \tag{B.8}$$

B.6 Drawdown Adjusted Growth

Within this thesis we propose a novel performance measure which we term *Drawdown Adjusted Growth*. The performance measure is suitable for evaluating geometric capital growth while penalising for large drawdowns. The DAG is calculated via Equation B.9:

$$DAG = \max(-log(MAX.DD) * r^g, 0) \tag{B.9}$$

A more detailed discussion of the DAG performance metric can be found in Section 6.4.4.

Appendix C

Interview with a FX Hedge Fund Manager

Transcript of an interview between the author (LB) and Dr. Christian von Strachwitz (CVS). Christian von Strachwitz is the CEO of Frankfurt based Quaesta Capital, a FX hedge fund specialising in managed accounts using a systematic trading method employing genetic algorithms.

The interview was carried out in April 2009, following the large carry trade drawdown during the period of the credit crisis. We omit parts of the interview which are irrelevant to the thesis.

LB   Do you trade carry strategies in your fund?

CVS   Not directly. Since we specialise in genetic algorithms for determining short-term FX trades, we do not focus on developing carry strategies at the moment. This will not change in the near future, especially since the reputation of the carry trade suffered a lot recently. Nevertheless, we can not exclude an exposure to the carry trade within the fund-of-funds product that we offer to our clients.

LB   What is your general view on the carry trade?

CVS   Nobody wants to hear anything about the carry trade at the moment. Everyone traded it and thus during the credit crisis many investors incurred large losses. Some fund managers traded the carry trade with high levels of leverage and no effective stop-loss- or risk-management mechanisms. At the moment the

industry is moving away from the carry trade and we do not intend to be the first institution to move against this trend.

LB   How do you know these facts?

CVS   In order to optimise our fund-of-funds product, we maintain and analyse a large data base of FX hedge funds performances. During the credit crisis, several funds disappeared from our database. Large losses forced them to liquidate. Also, many FX hedge funds are abandoning the carry trade. We know this by interpreting regression coefficients of FX hedge fund returns on e.g. proxies for carry trade returns. We find that the factor loadings on our carry trade proxy are declining for most FX hedge funds which survived the credit crisis.

LB   Do you think that market-timing could enhance carry trade returns?

CVS   We tested market-timing signals for FX carry trades based on simple risk factors. In our backtests the market-timing signals improved the risk-adjusted performance of the carry trade. Still, it is not our main interest to engage in carry trading activities at the moment.

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