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15

A METHODOLOGY FOR EARNING EXCESS RETURNS IN GLOBAL DEBT AND CURRENCY MARKETS WITH A DIVERSIFIED PORTFOLIO OF QUANTITATIVE ACTIVE INVESTMENT MODELS

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TABLE OF CONTENTS

THE LIST OF THE AUTHOR'S PUBLICATIONS AND CONFERENCE PRESENTATIONS

I. Research articles in international journals or books

1. **Vesilind, A**., 2007. The Profitability of Simple Trading Strategies Exploiting the Forward Premium Bias in Foreign Exchange Markets and the Time Premium in Yield Curves, in FindEcon Monograph Series: Advances in Financial Market Analysis (special editions of Acta Universitatis Lodziensis Folia Oeconomica, ISSN 0208–6018), No 5, Financial markets: Principles of Modelling, Forecasting, and Decision-Making, ed.-d by Milo, W and Wdowinski, P., Lodz University Press, 2007, forthcoming

II. Other refereed research articles

1. **Vesilind, A**., 2006. The Profitability of Simple Trading Strategies Exploiting the Forward Premium Bias in Foreign Exchange Markets and the Time Premium in Yield Curves, Eesti Pank Working Paper No 4. Indexed in EBSCO Business Source Complete, Google Scholar and RePEc databases.
2. **Vesilind, A., Kuus, T.**, 2005. Application of Investment Models in Foreign Reserve Management in Eesti Pank, Eesti Pank Working Paper No 6. Indexed in EBSCO Business Source Complete, Google Scholar and RePEc databases.
3. **Vesilind, A**., 2003. Application of fundamental models to money and exchange rate markets. University of Tartu, Faculty of Economics and Business Administration, Working Paper No 22. Indexed in EBSCO Business Source Premier, Google Shcolar, SSRN and RePEc databases.
4. **Vesilind, A., Toming, I., Lättemäe, R.,** 2001. Determinants of Estonian Sovereign Credit Rating. Eesti Pank Working Paper No 3. Indexed in Google Scholar and RePEc databases.
5. **Vesilind, A., Ehrlich, L.,** 2001. Determinants of Estonian Export of Goods: An Econometric Analysis and Comparison with Latvia and Lithuania. Eesti Pank Working Paper No 1. Indexed in Google Scholar and RePEc databases.

6. **Vesilind, A., Rell, M.,** 2000. Palga ja tootluse seosed majandussektoriti. Eesti Panga Toimetised nr. 2. Indexed in Google Scholar database.
7. **Sepp, U., Vesilind, A., Kaasik, Ü.,** 2000. Estonian Inflation Model. Eesti Pank Working Paper No 1. Indexed in Google Scholar and RePEc databases.

III. Conference publications

1. **Vesilind, A**. The Profitability of Simple Trading Strategies Exploiting the Forward Premium Bias in Foreign Exchange Markets and the Time Premium in Yield Curves, Conference "Forecasting Financial Markets and Economic Decision-making" 11–13.05.2006 Lodz, Poland, CD-ROM.
2. **Vesilind, A., Kuus, T.** Diversified Active Investment Decision-Making in Global Bond and Currency Markets: The Case of Eesti Pank, Conference "Forecasting Financial Markets: Advances for Exchange Rates, Interest Rates and Asset Management" 1–3.06.2005 Marseille, France, CD-ROM.

IV. Conference presentations

1. Conference "Forecasting Financial Markets and Economic Decision-making" 11–13.05.2006 Lodz, Poland. Title of article and presentation: Andres Vesilind "The Profitability of Simple Trading Strategies Exploiting the Forward Premium Bias in Foreign Exchange Markets and the Time Premium in Yield Curves"
2. Conference of young researchers in the Estonian Economic Association, 25–26.03.2006, Pühajärve, Estonia. Title of article and presentation: Andres Vesilind "Lihtsate struktuurset riskipreemiat kasutavate kauplemisstrateegiate tulusus valuuta- ja võlakirjaturgudel"
3. 25th International Conference Forecasting Financial Markets: Advances for Exchange Rates, Interest Rates and Asset Management 1–3.06.2005 Marseille, France. Title of article and presentation: Andres Vesilind, Toivo Kuus "Diversified Active Investment Decision-Making in Global Bond and Currency Markets: The Case of Eesti Pank"
4. 3rd Helsinki – Tartu Symposium on Economics 13.–14.5.2005 in Helsinki by EuroFaculty. Title of article and presentation: Andres Vesilind, Toivo Kuus "Diversified Active Investment Decision-Making in Global Bond and Currency Markets: The Case of Eesti Pank"
5. International Atlantic Economic Society conference, March 2004, Lisbon, Spain. Title of article and presentation: Attiat F. Ott, Andres Vesilind, Heiki Raadik "Asset Price Volatility and Policy Reaction: A Comparative Study".

INTRODUCTION

Motivation for the research

The returns on an investors' investment depend on overall market movements and on the movements of specific securities and/or specific speculative investment positions the investor has in his or her portfolio. The investor can choose to have no investor-specific positions and therefore earn an overall market return, or the investor can also choose to take specific views on specific securities (markets, market segments), which results in the investors' returns being different from the overall market average.

A passive investment strategy is a strategy that mirrors a market index (or any pre-given benchmark) and does not attempt to beat the market (benchmark) (www.investopedia.com). An active investment strategy is an investing strategy that seeks returns in excess of a specified benchmark by taking investment positions that differ from the market average (from a pre-given benchmark) (*ibid*). As the average excess returns relative to the benchmark from all active managers combined can not differ materially from zero[1] (with small deviations), then active management had historically relatively low share of attention.

However, this has changed during the last few decades. The low interest rate levels in the debt markets of developed countries[2] and declines in international stock markets[3] have markedly reduced the profitability of traditional passive fund management in developed markets. The small deviations from passive returns achievable by active management that were almost unnoticeable when passive return levels were high are becoming more and more noticeable with lower passive return levels. In addition, the passive holding of bonds has been

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[1] Investors, as a group, can do no better than the market, because collectively they are the market... – J. Clements, the Wall Street Journal, June 17, 1997.

[2] For example, the base interest rate level in the US was as low as 1% between July 2003 and June 2004, the yield on German 10-year government bonds was around 3% in September 2005 and the yield on Japanese 10-year government bonds was below 1% in the first half of 2003, Bloomberg data.

[3] For example, Standard & Poor's 500 stock index fell more than 47% from September 2000 to October 2002, the Nikkei 225 stock index fell more than 75% from December 1989 to April 2003 and the FTSE 300 stock index fell more than 55% from September 2000 to March 2003, Bloomberg data.

questioned during the last few years because of the very low interest rate environment around the world that corresponds to low current yield levels and potential loss of capital if interest rate levels should start to rise (Collins et al. 2005, p 75).

The potential returns from active management have increased further with the advent and growing popularity and liquidity of different derivative instruments. With high leverage levels different derivative instruments make it possible to earn large profits/losses even from small market movements. Therefore, we can conclude that with lower passive returns from one side and higher active returns available with the use of leverage and derivative instruments on the other side, the possibilities of influencing the total levels of return available to investors with active strategies deserves wider and more structured attention than has been the case up to date. This leads to the motivation of this thesis: A successfully structured active investment strategy for implementation using derivative instruments would enable investors to significantly improve the performance of their investment portfolios compared to the returns achievable from passive benchmarks.

Active investment decisions enable the investor to increase one's returns only if the investor manages to correctly forecast the movements in the markets (on average), or if tradable instruments exist whose risk – return ratio differs constantly from the market average. Therefore, active investment decisions assume the existence of at least minimal inefficiencies[4] in the markets. The existence of such inefficiencies is supported by the concept of rationally efficient markets (Grossman and Stiglitz 1980), which states that in order for the capital markets to be in equilibrium the search for inefficiencies has to be profitable. It means that investors who invest their time and resources in seeking market inefficiencies should be compensated with positive excess return.

The intensified search for excess returns from active management has led to a growing popularity and high growth in the number of investment funds specializing only in active management. The volume of funds under management in different hedge funds around the world (private investment firms that seek to gain high absolute returns by taking active positions in the markets) had grown to about 1.4 trillion dollars by 2006 (source: Hedge Fund Research, Inc). The rate of growth of the assets under management in different hedge funds has been about eight times as fast as that of more passive mutual funds: for example, the assets under management in different hedge funds grew by about 4 times between 1998 and 2003 (*ibid*), while the assets under management in different mutual funds grew by only about 50% during the same period (source: Investment Company Institute). The significant quest for higher returns has also drastically changed the investment portfolios of institutional

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[4] Market inefficiency: a situation when the price of a financial instrument is not equal to the true discounted value of its future cash flows (www.investopedia.com).

investors such as pension funds and insurance companies (Collins et al. 2005, p 75).

The profitability of active investment decisions depends on the market structure: the markets where the share of speculators and other investors with the return as their main goal is the highest, offer the smallest chances for excess returns from active management. For example, this is the case with stock markets where the main goal of market participants is to achieve higher return per risk. The structure of debt and currency markets is somewhat different as a large share of transactions in those markets is carried out without return as the main goal. For example, the decisions of central banks to change monetary policy interest rates are motivated by the goals of influencing inflation, economic growth and/or the exchange rate of the domestic currency. The foreign exchange transactions between corporations are often motivated by the goal of minimizing the volatility of future returns or input costs, etc. (Collins et al. 2005, p 75). These and other non-profit-motivated transactions can create inefficiencies in debt and currency markets and make these markets more suitable for earning excess returns with active investment decisions.

This thesis focuses only on the markets where the possibilities of earning excess returns with active investment decisions are the highest (i.e., in the debt and currency markets) and does not deal with stock markets. Because active investment strategies can be implemented with the lowest costs in countries where liquid derivative markets exist, only the markets of the ten most developed regions (the USA, the UK, Eurozone, Sweden, Norway, Canada, Japan, Australia, Switzerland and New Zealand) are considered.

Active investment decisions can be based on subjective judgment of market situation, or on systematic, rule-based guidelines estimated from historical relationships. Only rule-based decisions based on previously tested quantitative relationships are considered in this thesis because their expected risk and return statistics can be calculated using historical tests.

Based on the Law of Active Management (Clarke et al. 2002, p 50), the risk-return ratio of actively managed portfolios is positively dependent on two factors: the risk-return ratio of each individual active investment strategy and the number of different non-correlated active investment strategies. Therefore, two ways of improving the performance of actively managed portfolios exist: 1) to improve the risk-return ratios of individual strategies or 2) to increase the number of uncorrelated strategies. The first of these two possibilities is relatively more difficult to achieve because of the high effectiveness of capital markets[5]. Therefore, this thesis focuses systematically and thoroughly on the second possibility and shows that although it is difficult to profit consistently

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[5] For a review of the early studies on the efficiency of the capital markets of advanced economies see, for example, notes 40-114 in Saari (1977) and for more recent reviews see Fama (1997) and Malkiel (2003).

from one strategy due to the efficiency of financial markets, consistent excess returns can be generated from the inclusion of multiple currencies, multiple debt securities and/or multiple markets in general.

Although previous studies exist where the benefits of combining different investment models are shown (for example, Ilmanen and Sayood 2002, Ilmanen *et al.* 2002), these studies have only used a few different models. The present thesis goes one step further and widens the portfolio of diversified quantitative active investment models to incorporate systematically both single- and multi-factor models, models with fundamental economic inputs and models with the time series of financial instruments as the only inputs, models that try to time the markets movements, and models that try to exploit existing structural inefficiencies[6] and different types of investment models: econometric, technical and ranking.

With the combination of the different approaches of academic and professional finance and the combination of different investment models into one unified and integrated approach, this thesis is also an important step in a new research field called "Intelligent Finance." This research field tries to show that both the academic finance theory of efficient markets and professional papers showing the predictability of financial time series may be simultaneously valid (for a further description of the subject see Pan 2005, p 5 and Pan *et al.* 2006).

The aim and research tasks of the thesis

The aim of this thesis is to develop, using the "Intelligent Finance" approach, a methodology for earning positive and stable excess returns with active investment decisions. The methodology will include a development and testing of a diversified set of quantitative active investment models, tests of different methods for combining the models into one investment portfolio and guidelines for interpretation and measurement of performance. The methodology developed can be applied to increase the returns on investments by various investors, including central banks, pension funds, insurance companies and different hedge funds.

To achieve this aim, the following research tasks are set:
1) To analyze the theoretical foundations of the methodologies for earning positive excess returns with active investment strategies.

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[6] A structural inefficiency denotes situations where a certain risk exposure is undervalued (and overcompensated) compared to its risk level for a longer period of time due to structural differences in supply and demand relationships or some other structural and long-lasting factor in the given asset class.

2) To analyze the efficiency of, and the expected probability of earning excess returns with active investment strategies from various markets: equity, interest rate and foreign exchange markets.
3) To analyze different investment styles and the quantitative active investment models that have been proposed and/or tested in previous literature.
4) To set up a theoretical framework for empirical estimation that would include active investment models using different investment styles, different markets and a diversified set of inputs.
5) To estimate a diversified set (portfolio) of active investment models.
6) To analyze the possible ways of combining different active investment models.
7) To combine the estimated models into one portfolio and to draw conclusions about the performance and diversification benefits of the entire portfolio of models.

The following assumptions apply throughout the thesis:
- Due to liquidity considerations only the ten largest and most advanced developed economic regions in the world (The USA, Eurozone countries (represented by Germany throughout the thesis), Japan, Canada, The UK, Sweden, Norway, Australia, New Zealand and Switzerland) are considered.
- Because of the lower share of market participants with speculative goals, the active risk positions (i.e., investment positions that differ from a pre-defined benchmark portfolio) are taken only in interest rate or foreign exchange markets in the abovementioned regions and currencies.
- No credit risk is allowed, except for counterparty risk in transactions using swap and/or forward contracts, which is considered to be zero.
- All the active investment positions are taken with the following derivative instruments: swap, forward, or futures contracts. Different options were left outside the scope of this thesis, although in principle these instruments can also be used for taking investment positions. The benchmark portfolio of the investors' funds is invested separately from the active portfolio and its most liquid part (invested in money market instruments and deposits in the abovementioned countries) acts as collateral for the positions in derivatives.
- Because all the positions can be scaled according to the investors' risk tolerance, the subject of risk measurement and risk control is outside the scope of the thesis.

The abovementioned characteristics can describe a highly leveraged hedge fund, but they can also describe a portfolio manager in a very conservative investment fund or even a central bank as long as the positions are taken and scaled according to pre-defined risk limits. Using derivative instruments for taking positions enables the easy measurement of investment results as the results can be compared to a zero return.

The structure of the thesis

This dissertation consists of two major parts. The first part formulates the theoretical background for the estimation of the portfolio of active investment models and the second part estimates empirically a diversified portfolio of active investment models. The general logic of the thesis is shown in Figure 1.

Theoretical foundations of the methods for earning positive excess returns with active investment strategies (Ch. 1.1)	The overview of different possibilities for getting investment signals (Ch 1.2)

Overview of different quantitative models:
- "Fair value" models and models based on past price data (Ch 1.3)
- Quantitative investment models for taking foreign exchange risk (Ch 1.4)
- Quantitative investment models for taking interest rate risk (Ch 1.5)

Theoretical portfolio of active investment models (Ch 1.6)

Description of estimation period and methodology (Ch 2.1)	Empirical estimation of active investment models: • Models based only on the price data of traded instrument (Ch 2.3) • Single-factor investment models with fundamental inputs (Ch 2.4) • Multi-factor investment models with fundamental inputs (Ch 2.5)
Analysis of market data, trading costs and liquidity (Ch. 2.2)	

Creating a single portfolio of separate investment models (Ch 2.6)

Figure 1. The general logic of the dissertation

The theoretical part consists of the four steps needed to build a theoretical methodology for earning excess returns in global debt and currency markets with the help of a portfolio of quantitative active investment models. First,

subchapter 1.1 analyzes if and under which conditions active investment strategies can yield stable positive results. Based on the concept of rationally efficient markets (Grossman and Stiglitz 1980) and on the difference in the share of market participants with profit maximization as their most important goal, the following conclusions are made: 1) financial markets do have minuscule inefficiencies and 2) there is a higher chance of finding inefficiencies in foreign exchange and interest rate markets than in equity markets. Based on the Law of Active Management (Clarke *et al.* 2002, p 50), an additional hypothesis is made that when we combine many different investment models that try to earn excess returns from existing minuscule inefficiencies in the markets, the performance of the combined diversified portfolio of such models may be sufficiently stable and consistent for actual implementation.

Subchapter 1.2 analyzes the different possibilities of receiving investment signals using different investment styles (systematic vs. discretionary) and using different inputs (macroeconomic fundamentals vs. past price data). As only the systematic investment style based on quantitative investment models or strategies can be objectively back-tested, the discretionary analysis of financial markets is left outside the scope of the thesis.

Subchapters 1.3–1.5 give a more detailed overview of previously developed quantitative investment models. The analysis starts with the analysis of different quantitative "fair value" models (subchapter 1.3.1) and quantitative models based only on price data (subchapter 1.3.2). The analysis continues with the overviews of quantitative models also using fundamental inputs: subchapter 1.4 for models covering foreign exchange markets and subchapter 1.5 for models covering interest rate markets.

Subchapter 1.6 analyzes the relative importance of different investment styles and briefly describes previous attempts to build a diversified investment portfolio out of multiple models (subchapter 1.6.1). The chapter ends with a compilation of the theoretical portfolio of active investment models for empirical estimation (subchapter 1.6.2).

The empirical part of the thesis starts with the description of the methodology used and an analysis of the trading costs and liquidity of the markets considered in this thesis (subchapters 2.1 and 2.2). After that, different investment models are estimated and tested: models based mainly on price data (subchapter 2.3), single-factor models using economic variables (subchapter 2.4) and multi-factor models using economic variables (subchapter 2.5). Within the models using only price data two subsets of models are estimated: pure technical models (subchapter 2.3.1) and ARMA models (subchapter 2.3.2). Within the single-factor models using economic variables a model for taking foreign exchange (FX) risk is estimated in subchapter 2.4.1 and for taking interest rate (IR) risk in subchapter 2.4.2. Within multi-factor models using economic variables a model for taking FX risk is estimated in subchapter 2.5.2 and models for taking IR risk in subchapters 2.5.2 (model for duration

positions), 2.5.3 (model for yield curve positions) and 2.5.4 (model for cross-country yield spread positions).

Subchapter 2.6 studies different possibilities for combining separate investment models into one investment portfolio. Two theoretical approaches (traditional portfolio theory and leptokurtic portfolio theory) are used and compared to a more simple ("benchmark") setup using only the number of instruments used (traded) in each model. Furthermore, in this subchapter the benefits of diversification are shown and the hypothesis that a diversified portfolio of quantitative active investment models for trading using derivative instruments in the currency and debt markets can yield sufficiently stable excess returns to investors for implementation in actual trading is verified.

Overview of data used and methodology

The methodology developed in the thesis follows partly the "Intelligent Finance" approach proposed by Pan *et al* (2006). It combines the findings of academic research, findings from previous empirical studies and the results of previously developed investment models by bigger global investment banks. The thesis uses both financial time series and macroeconomic variables as inputs and combines the two most important schools of thought in developing trading models: fundamental analysis and technical analysis.

The time series of economic and financial variables (instruments) used in the thesis come from three sources: the news and data platform "Bloomberg", database "Reuters EcoWin" and monthly forecasting journal "Consensus Forecasts". The data on the liquidity and market depth of traded instruments is estimated based on real-time bid and ask quotes of market participants as provided by Bloomberg (observation time: June 2006, normal trading hours). The data on trading times is also taken from Bloomberg (function "DES").

Bid-ask spreads on different electronic trading platforms offered to institutional investors (observation time: June 2006, normal trading hours) are used as a source for estimating trading costs. For calculating the average spread in foreign exchange markets the following trading platforms are used: Citibank's platform "FX Trader", Dresdner bank's platform "Click and Trade" and UBS bank's platform "FX Trader". For calculating trading costs in interest rate futures' markets ABN AMRO bank's[7] platform "NetOMS" and Barclays Capital's platform "BARX Futures" are used.

The models in the empirical part are estimated using various statistical packages. For estimating the technical trading rules based on moving averages MS Excel is used. The econometric models based on ARMA methodology is estimated using EViews 5. Single-factor models and multi-factor models based

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[7] By the time of the publication of this thesis, the platform "NetOMS" was acquired by UBS.

on the simple ranking of the input variables are tested using MS Excel. Econometric interest rate models taking duration and yield curve spread positions are also estimated using EViews 5.

All the models are tested on derivative instruments: futures, forward or swap contracts. As the forward or swap contracts do not cost the investor anything at the moment of initiation and the margin accounts for the futures' positions the investor has earn interest for the investor equal (or similar) to the interest rate level on deposits and/or other money-market instruments, then the results of the estimated models represent pure excess returns that can be earned over the returns of the passive investment portfolio. The use of derivative instruments also makes it easy to separate the different risk components: currency risk, duration risk, yield curve risk and cross-country yield spread risk, thereby eliminating the fluctuations caused by other components.

All the models are tested during a 14-year (168-month) test period starting on December 31, 1992 and ending on December 31, 2006.

Theoretical and practical limitations

The limitations of this thesis are mainly practical. There is constant pressure by market participants to erode the factors and models used to predict market dynamics. "Any strategy yielding above-average risk-adjusted return […] is, by the unshakable laws of human nature, under a sustained threat by other market participants seeking to correct this "inefficiency".[…] This means that there is a limited shelf life for nearly any highly successful market approach."(Grant, 2004, p 10).

In quantitative terms, the information ratio[8] of any factor which has demonstrated reasonable performance in the past can decline. Therefore, it is necessary to constantly monitor the performance of the models and input factors and adjust the investment program if necessary (when its performance significantly declines). For example, the performance of managers who extensively use various trend-following models shows how the performance of a model-based investment strategy can diminish over time. According to the CISDM[9] data of 1983–1993, the average annual return of the trend-following commodity trading advisors (CTAs) was 19.1%, but in the next sub-period (1994–2004) it decreased to 10%; i.e., almost by a half (Centre for … 2005).

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[8]   A measure of excess performance achieved against additional risk taken relative to a benchmark. Usually calculated using the formula developed by W. F. Sharpe (Sharpe 1994, also called the "Sharpe ratio").
[9]   Center for International Securities and Derivatives Market at the University of Massachusetts.

In recent years an important factor influencing market behavior has been the rapid growth of hedge funds, which have increasingly exploited existing market inefficiencies. A study by JP Morgan (Loeys and Fransolet 2004) found that in recent years many better-known market opportunities have been eroded in the two categories where the hedge funds have been most active: equities and interest rate markets (*ibid,* p 1). Furthermore, in foreign exchange markets it has been found that the predictive power of indicators based purely on public information has declined during the last few years, while the inputs with some proprietary value have retained their usefulness (Normand *et al.* 2004, p 2). According to the study by Loeys and Fransolet (2004*,* p 29), publicly available factors like carry[10], change in economic activity expectations, etc. (that were reliable predictors of forex market behavior in 1994–1999), demonstrated a lower information ratio for forecasting price dynamics in 2000–2004 when hedge fund activity became stronger. The same was reported for simpler technical trading rules (Olson 2004). At the same time, some other, more proprietary factors (like portfolio flows, changes in speculative positions, etc.) gained more importance as measured by their information ratio.

This process has been accompanied by declining volatility in some markets and also led to a higher correlation between major financial markets that reduces the opportunities for cross-market trades. Therefore, we can conclude that the changes in market environment and the intensification of search for excess returns can cause any of the estimated models to fail in the future. To avoid that, constant work aiming at maintaining a competitive edge in the market is needed.

Acknowledgements

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[10] Carry trade: A strategy in which an investor sells a certain asset with a relatively low interest rate and uses the funds to purchase a different asset yielding a higher interest rate. A trader using this strategy attempts to capture the difference between the rates, which can often be substantial depending on the amount of leverage the investor chooses to use (www.investopedia.com).

1. THEORETICAL METHODOLOGY FOR EARNING EXCESS RETURNS IN GLOBAL DEBT AND CURRENCY MARKETS

1.1. Theoretical foundations of the methods for earning positive excess returns with active investment strategies

1.1.1. The possibility of earning excess returns with active investment strategies

Passive and active investment strategies, having already been defined in the introduction, differ from each other in the following ways (www.investopedia.com):

- A passive investment strategy is a strategy that mirrors a market index (or any pre-defined benchmark) and does not attempt to beat the market (benchmark).
- An active investment strategy is an investing strategy that seeks returns in excess of a specified benchmark by taking investment positions that differ from the market average (from a pre-defined benchmark).

In practice a passive strategy means that the investor holds his or her funds at all times in a pre-defined portfolio that corresponds to the long-term risk, return and liquidity targets of the investor. In this way, the investor earns the return of the pre-defined benchmark minus the costs associated with custody accounts and trading. Active management means that the investment portfolio can deviate from the pre-defined passive portfolio; therefore, it can earn a higher or lower return than the passive portfolio. Excess return, as is used in this thesis, is the difference between the return of the actively managed portfolio and the return of the pre-defined passive benchmark portfolio.

These decisions to actively deviate from the benchmark portfolio are made with the goal to better profit from the opportunities which might develop in the markets. These opportunities may be related to changes in the economic cycle, certain economic or market scenarios, events, etc., which influence the prices of the securities. An active investor attempts to predict these factors or reacts to them and adjusts his portfolio accordingly so that it would be more profitable than a simple passive strategy. These adjustments can be made by swifting real funds between different financial instruments – for example, selling a security that is in the benchmark portfolio and buying another that is not, or these

adjustments can be taken with derivative instruments that need little or no underlying capital and can subsequently be implemented so that the benchmark portfolio itself is not affected.

The second possibility has several advantages over the first one, mainly connected to the fact that the risk and return from active and passive decisions can be clearly separated. In fact, the actual structure of a passive portfolio becomes irrelevant in the measurement of the risk and return of the active decisions, as long as the passive portfolio has enough liquid funds to act as collateral for the active decisions. In this case, the return of the derivative portfolio is equal to the excess return and the knowledge of the exact structure of the passive portfolio is not needed to analyze the profitability of active decisions.

Any single active investment strategy may perform better or worse than the passive strategy. However, as W. Sharpe (1991, p 7) points out, the same can not be said of the cumulative (or average) performance of all active investment strategies together: "If "active" and "passive" management styles are defined in sensible ways, it *must* be the case that:

1) before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar and
2) after costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar"

This statement is based on the logic that all active and passive investors together make up the whole market and because the return of passive investors does not materially differ from the overall market return, while the average return of active investors also can not differ materially from said market return (before costs).

Therefore, the average active excess returns from all active managers together before costs can not differ materially from zero, because the excess return earned by one investor having a different position from the "market portfolio" has to be offset by another investor(s) having an opposite position resulting in a loss. And even more – as active management often means higher costs than passive management (mostly related to additional staff, training, software, trading, etc.), then for active management to be meaningful it is not enough if the average returns from active decisions are positive – the additional profits have to also be large enough to cover the increase in transaction costs and other outlays.

Most of the empirical tests made to date support the above-described logic and as W. Sharpe (1991, pp 8–9) points out, "Properly measured, the average actively managed dollar must under-perform the average passively managed dollar, net of costs. Empirical analyses that appear to refute this principle are guilty of improper measurement". But the fact that, on average, the market can not be beaten does not necessarily mean that excess returns can not be earned by *some* skillful managers. But this would demand the existence of market

participants who make repeatedly incorrect decisions and are "willing losers" either because of their lack of skills or because they have other primary motives than profit maximization[11].

Research shows that the percentage of actively managed mutual funds that under-perform the market is as high as 95 percent (Thorley 1999).[12] In addition, there are a lot of articles (for example, Fong and Young. 2005, Neely and Weller 2003, etc.) where the researchers take one certain active trading rule, add the transaction costs and find that the rule does not yield statistically significant additional profits compared to a simple passive buy-and-hold strategy. Furthermore, there are many papers (for example, Kolb and Stekler 1996, etc.) where directional forecasts from some forecasting model (or from some certain forecaster(s)) are compared to random coin-flipping forecasts with results that indicate that the accuracy of such forecasts is statistically not significantly different from 50%.[13]

It has been also tested whether professional managers as a group are more skilled than individual managers and if they can earn positive excess returns while taking advantage of the wrong investment decisions of non-professionals. The results (for quotations see Waring and Siegel 2005, p 23) show that it is not the case – the average excess returns of professional managers are negative after costs and fees.

1.1.2. The differences in the profitability of active management in stock, interest rate and foreign exchange markets

Although the majority of the literature described in the previous subchapter doubts the possibility of earning positive excess returns with active investment

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[11] The school of thought in the financial markets that seek to take advantage of passive, non-profit-maximizing market participants using active speculation and game theory is also called "Strategic Analysis" (Pan 2006, p 274).

[12] The results are similar when we consider companies that specialize in achieving active excess returns (hedge funds, future funds and commodity trading advisors) instead of mutual funds. For example, the results (as of July 31, 2005) of the average performance of hedge funds, commodity trading advisors and future funds by different trading styles, economic sectors and/or regions monitored by the Centre for International Securities and Derivatives Markets (CISDM) show that within last 10 years only 5 hedge fund samples out of 14, 1 trading advisor sample out of 10 and 0 future fund samples out of 6 outperformed the Standard & Poor's 500 index.

[13] In addition, the author has investigated the accuracy of interest rate forecasts published in "Consensus Forecasts" journal between 1995 – 2000 (Vesilind 2001). The results were: 1) the 3-month-ahead forecasts taken from professional forecasters as published in "Consensus Forecasts" are less accurate than no-change predictions made using the actual interest rate level from 3 months earlier and 2) the directional accuracy of the forecasts of 10-year government bond interest rates 12-months-ahead taken from professional forecasters as published in "Consensus Forecasts" is less than 50%.

strategies, we can see that the majority of it is written using a sample of managers holding stock portfolios. It is natural to assume that there are not many "willing losers" among stock market participants. It is also natural to assume that there are not many "willing losers" because of the lack of skill in foreign exchange and interest rate markets. Investors do and will learn and most of the investors earning less than benchmark returns will eventually change their investment strategy.

However, with "willing losers" who earn less-than benchmark returns because they do not have profit maximization as their most important goal, the situation in the bond and currency markets is somewhat different than in equity markets. Furthermore, the results reported from empirical studies on interest rate and foreign exchange markets differ somewhat from the results presented in studies made using equity market data: for example, the persistence of positive or negative excess returns among bond markets has been documented in a study by Huij and Derwall (2006) and there are many trading strategies and active investment models reported to have stable excess performance in exchange rate and interest rate markets (for quotations see Bianchi 2004, p 90 and the corresponding overview chapters of this thesis). The main reason for that is the relatively greater size of non-speculative capital flows with profit not as the main goal in the bond and currency markets than in the stock markets.

The relative share of non-speculative capital in currency markets is high, because two of the largest market participants in this market, namely central banks and corporations, have no direct motive for profits when buying and selling currencies: for the former the currency is an economic policy tool, whereas the latter uses the foreign exchange market to translate revenues or hedge some costs into its balance sheet (Collins et al. 2005, pp 6, 75).[14] It means that central banks are willing to earn below benchmark returns on their reserves in order to fulfill other goals – to stabilize the exchange rate of the domestic currency, to target inflation or to target a specific level of economic growth. Corporations in turn are willing to lose on average on foreign exchange transactions in order to avoid balance sheet fluctuations or just to get a cross-border deal (it can be a purchase or selling transaction of a good or service or some investment deal) done. To a smaller extent we can also add international tourists, private investors seeking international exposure to foreign stocks and bonds and investors passively hedging the exchange rate risk on their foreign stock and bond holdings to the "willing losers" group in currency markets. (Collins et al. 2005, p 31, Rozanov 2004, p 3).

Based on a survey by BIS (BIS 2005, p 12) the structure of the foreign exchange market in 2004 was the following: 14% of turnover was with non-financial customers, 53% was between market-makers and 33% with other

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[14] At the same time corporations are usually profit motivated in other markets and business areas that constitute their "core" business.

financial institutions. The market-makers themselves do not trade for speculative profit in foreign exchange markets. The same can be said of the majority of non-financial customers, as their main goal in foreign exchange markets is to exchange the funds for or to reduce the price risk of the inputs or outputs of their main business. However, the study (*ibid,* p 13) states that the rise of the share of non-financial customers from 11% in 2001 to 14% in 2004 might in part have been driven by corporate treasurers starting to follow speculative investment strategies common among financial investors. This means that up to 3% of foreign exchange market turnover may be between non-financial customers speculating in FX markets.

The majority of financial institutions that make up the 33% of the entire foreign exchange market turnover are institutions that also do very few trades in the foreign exchange market in order to earn speculative profit: central banks, fund managers, custodians and pension and insurance companies. In addition, there exist regulations that directly prohibit these financial institutions from taking direct foreign exchange risk. For example, the Third Financial Market Promotion Act in Germany prohibits German investment trusts from carrying out currency transactions that are separate from an underlying investment instrument and in France pension funds are not allowed to hold short foreign exchange positions (ECB 2003, p 25).

Institutions that are allowed to and do actively take speculative positions in foreign exchange markets are different hedge funds, commodity trading advisors and currency overlay managers. Their share in the daily turnover of FX markets is estimated to be as low as about 5% (Collins et al. 2005, p 65). Although published in 2005, this 5% seems to be calculated based on an earlier study of BIS (2002), where the share of financial institutions in total turnover was 28%. The study in 2005 states that the rise in the share of financial institutions (from 28% to 33%) was mainly caused by a broad search for yield from carry and momentum strategies (BIS 2005, p 13), which means that the share of financial customers trading in FX markets for speculative profit might have risen from 5% up to 10% by 2005. Therefore, we can assume that the share of market participants with speculative return as their main goal together with the non-financial customers trading in FX markets for speculative profit is not higher than 13%.

Consequently, the share of "willing losers" in currency markets is large enough to create inefficiencies to the benefit of currency specialists. The inefficiencies are further increased by the fact that there is little consensus on the correct fundamental value of any specific currency at any specific moment and a substantial amount of research (for example, MacDonald 1999 and the citations therein) showing that currencies can deviate from their "fundamental values" for extended periods of time. Altogether, it creates an environment where those with superior modeling skills can earn additional profits from the inefficiencies in currency markets (Dales and Meese 2003, p 2).

Central banks are also the largest non-speculative market participants in interest rate markets as they act actively in debt markets by setting base interest rate levels. Besides central banks, the investments of other governmental institutions often have the preservation and liquidity of their capital as their first investment goal instead of return, which also supports the inefficiencies in the safe and liquid government bond markets of advanced economies.

In some respect many pension funds are also more focused on just matching with minimum risk level the future liabilities than on more risky profit maximization. A good example here was the wide-spread activity of European pension funds in the 1st half of 2005, when long-term (10+ years) bond yields in Europe were falling rapidly and approaching the very low level of 3%. Instead of switching the investments into lower-maturity debt instruments that would have given more price protection if the yields had happened to rise in the future, most of the pension funds were actively buying longer-term bonds with the reasoning that they were better off with "locking in" a 3% return level for the next ten years than risking a chance of further decline in interest rate levels (source: author's discussions with different European pension fund managers during different investment seminars and conferences). Such behavior was the most widespread in the Netherlands where many pension funds have a minimum guaranteed return requirement of 3% or 4% (www.aegon.com/ about/productlines/14240/26057/), which creates a risk bias. For example, with a 3% required guaranteed return level the pension fund manager may prefer buying and holding a 10-year government bond with a return level of 3.1% (at purchase moment) until maturity than to engage in more active and riskier strategies with expected return levels of, say, 3.2% during the next 10 years[15]. It means that also in the government bond markets of major advanced economies there may exist enough "willing losers" for active management strategies to be profitable.

We can argue what the reasons are and why the existence of such "willing losers" in foreign exchange and interest rate markets is not being fully exploited yet by speculators. The reasons may include (but are certainly not limited to) different trading restrictions that many big mutual funds have: for example, restrictions that do not allow one to take an open exchange rate risk in an amount in excess of the funds invested in any given region (i.e., fund managers can use a currency overlay only for risk management and "hedge" the currency

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[15] Although there are no required return levels for pension funds in Estonia, the not very best preference (economically) toward longer-term bonds in the declining yield environment during the first half of 2005 was also widespread among managers of Estonian conservative pension funds. It resulted in a big yearly cumulative decline in the net asset value between 1.07.2005 – 30.06.2006 of the shares of both two biggest conservative pension funds – Hansabank's K1 and SEB banks conservative fund (12-month NAV changes were correspondingly –5.60% and –4.18%, data source www.pensionikeskus.ee).

risk of a stock or bond investment with a hedge ratio of between 0% and 100%, but not above or below that amount), restrictions on the use of derivatives, restrictions that limit the set of available markets, restrictions on trading cross exchange rates (cross-country interest rate spread views) outside the domestic currency (domestic bond market) and/or restrictions on the short-selling of securities the investor does not yet own. These trading restrictions limit the possibilities of diversification and the limitations on the use of derivatives also increase the share of trading and other costs in excess returns, because the use of derivatives usually means leveraged returns with about the same level of costs that are needed to take real-money investments.

However, the fact that the inefficiencies in the foreign exchange and interest rate markets do yet exist does not mean that the constantly increasing number of speculators trying to exploit them does not have any effect on the profitability of simpler active trading strategies. Many studies (Loeys and Fransolet 2004, Normand *et al.* 2004, Olson 2004, etc.) have found that the predictive power of many simpler indicators based purely on public information has declined over time. Therefore, we can conclude that the amount of inefficiencies available to profit from is getting smaller over time and for continuous success active managers need to constantly monitor the performance of existing trading strategies, leave the strategies that have become too widely used and constantly develop new strategies to replace the ones that have lost their profitability due to their too widespread use.

1.1.3. Passive and active return in interest rate and foreign exchange markets

For bond investors there are both passive and active investment returns. Active returns are those resulting from the decisions to buy the bonds of other countries, bonds with different durations or bonds with different credit ratings (or from taking corresponding or other interest rate views with derivative instruments) than the pre-defined structure of the benchmark portfolio and these active returns are usually smaller in absolute amounts than the returns from passive management, unless the investor takes exceptionally high leverage levels or an excessively high currency risk. Therefore, for bond managers the returns from active management are usually only a supplement to the passive returns that make up the majority of the total return. For bond managers, consistent if modest predictability in excess returns from active management is described in a paper by Ilmanen and Sayood (Ilmanen and Sayood 2002, p 40).

The discussion whether currencies can be considered as a separate asset class has led to different conclusions during different time periods. Historically, currencies were not viewed as a strategic asset class because they do not have positive expected returns from just passive "buy-and-hold" style investing that bonds have. Therefore, currencies were considered tactical assets rather than

strategic, as some kind of active management is the only way to unlock the returns that may be generated out of them. However, more than 27 years of currency market returns data with low correlations to the returns of other asset classes has changed this view. Currencies are also being viewed more and more as a possible separate strategic asset class (see Collins *et al.* 2005 and Panholzer 2004).

Although it is sometimes argued that forecasting the movements in exchange rates is extremely difficult and no factor has been found to be consistently useful in forecasting exchange rates over substantial periods of one or two years (example: Greenspan 2002), there are many studies that show the opposite. For example, a study of 152 active currency managers made in 1998 (Strange (1998)) shows that currency overlay managers[16] add value fairly consistently and over a long period of time. On average, 80% of the accounts studied outperformed their benchmarks[17] with an annualized average value added of 2.4% (*ibid,* p 1–2).

The performance of active currency managers is continually being monitored by Parker Global Strategies. Their index currently includes 66 programs managed by 45 firms located in the US, Canada, UK, Ireland, and Switzerland and shows an average risk-adjusted annual performance (pure excess return) of 10.9% on average between 1990 – 2004 (Collins *et al.* 2005, p 6) and 1.83% during the last 36 months (Parker Global Strategies web-site, data as of September 2005). According to the Parker index, the pure excess returns of currency managers are positive both for managers using a systematic and discretionary investment style, annual risk-adjusted performance was 1.74% and 2.31%, respectively, during the last 36 months (*ibid*). A paper by Collins *et al.* (2005, p 3) states directly that "Opportunities exist to make money in deep and liquid currency markets where investors have skill and specialization." A paper by Sarantis (Sarantis 2006, p 2276) states that "Investors could have made statistically significant profits in currency markets during the 1990s … even allowing for transaction costs and risk factors" and a paper by Rozanov (2004, p 4) states "impressive evidence of broad-based out-performance … with positive success ratios, consistent excess returns and low tracking errors." A paper by Dales and Meese (2003, p 2) states that even the 75th percentile currency manager has had positive performance over horizons greater than 1 year. Academic evidence indicating the possibilities of earning excess returns in foreign exchange markets can also be found in more distant history; for example, in a book by Surajaras and Sweeney (1992).

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[16] (Usually outsourced) managers who manage only the currency risk of the investor. The returns from such active currency positions are "overlaid" on the other returns from the investor's investments (www.investopedia.com).

[17] The respondents in a study by Strange (1998) answered only to the question if, and by what amount, they outperformed their benchmark. The benchmark itself was not disclosed and may have been different among different respondents.

The argument that certain inefficiencies do exist in financial markets and that these inefficiencies can be profitably exploited with proper skills to make active management meaningful is also supported by the "rational efficient market formulation" theory (Grossman and Stiglitz 1980). It says that in an equilibrium there has to be an "equilibrium amount of inefficiencies" in the markets. The "equilibrium amount" should be big enough to reward the investors seeking these inefficiencies and paying the additional costs of gathering and analyzing additional information with higher gross returns. When the markets become less efficient, then the number of "speculators" seeking inefficiencies rises and as they exploit the existing inefficiencies, the markets become more efficient. Vice versa – in the markets that are very efficient a portion of "speculators" will find the work of seeking inefficiencies unprofitable and they will change their investment style to passive indexing, resulting in markets becoming less efficient. The same concept applies to the existence of direct arbitrage opportunities in interest rate and foreign exchange markets (Akram *et al.* 2006).

The use of active management strategies may be attractive to investors also because the returns from these strategies usually have a low correlation with the returns achieved from the benchmark (passive) investments (Collins *et al.* 2005, p 6). For example, the correlations between active currency returns and stock market returns have been as low as 0.02 to 0.08 between 1995 and 2005, depending on the stock market index used (*ibid*, p 34). At the same time, it has to be remembered that it may take a relatively long time for the higher returns from active investment strategies to materialize[18], which makes them unsuitable for many fund managers whose performance is evaluated over relatively short time spans. As the costs that occur with active management (research, labor, time, trading, etc.) have a low dependence on the leverage level of the active positions taken, then we can conclude that a successful active management strategy should have a maximum amount of leverage (in order to reduce the share of costs in active returns) and be based mostly on derivatives.

The majority of possibilities for earning active excess returns are connected either to different time-varying risk premiums or market inefficiencies driven by systematic behavioral biases. Therefore, many strategies include carry and value indicators linked to required risk premiums or momentum and under-reaction patterns that can be linked to behavioral biases (Ilmanen and Sayood 2002, p 41).

1.1.4. The importance of diversification

The reason for a deviation in the views on the predictability of exchange rate movements may also lay in the fact that in a large share of theoretical literature

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[18] There are very few active investment strategies (models) that have generated profits in all rolling 12-month time intervals within simulation or implementation periods.

the attention is focused mostly on active management *within* asset classes (Darnell *et al.* 1997, p 2); for example, on the predictability of any single exchange rate pair. In bond markets many investors waste the "free lunch" of active diversification by concentrating their risk excessively and inefficiently on bond market direction (Ilmanen and Sayood 2002, p 40).

Most investment managers at the same time can implement their views across many markets. This leads us back to the hypothesis described in the chapter on the motivation of this thesis: that although due to the efficiency of financial markets it is difficult to profit consistently in one market with one strategy (for example, using one investment model on the movements of one exchange rate pair or interest rate), consistent excess returns can be generated by applying multiple investment models on multiple currencies, multiple debt securities and/or multiple markets in general. By combining different approaches, models and markets, this approach, called "Intelligent Finance," tries to eliminate the very last risk in investment management – the incompleteness of an investment or trading method or system (Pan *et al* 2006, p 273).

The efficiency of active management can be characterized by the information ratio (InR), defined as expected active return divided by active risk. The relationship between the information ratio of a combined portfolio and its zero-correlated subcomponents has been summarized as the Law of Active Management (Clarke *et al.* 2002, p 50):

$$InR \approx IC\sqrt{N} \qquad (1)$$

where: *InR* is the information ratio (ratio of average excess profit to its volatility) of the entire investment portfolio;

IC is the information coefficient defined as the correlation between the forecasted excess return and the actual excess return;

N is the number of independent investment decisions.

In a more general case (see Buckle 2004) N is replaced with a wider measure, BR or "breath," that also allows for the following situations: a) one forecast is applied across many assets, b) forecast errors are correlated or c) both forecasts and forecast errors are correlated. In special cases where forecast errors are mutually independent, BR=N and if the forecast errors have a correlation of 1, then BR=1.

According to the Law of Active Management, the performance of an actively managed portfolio can be improved either by improving the performance of individual investment decisions [or models] (i.e., by increasing their predictive power) or by increasing the number of independent (in practice, weakly correlated) investment decisions [or models]. We can also illustrate this

relationship graphically (see Figure 2)[19]. In the figure the cumulative probability of earning a positive excess return from nine simple "investment models" is simulated. Each "model" produces uncorrelated investment signals with a normally distributed excess return for the investor. The models differ from each other in respect of their predictive power, measured as the probability of getting an excess return greater than zero (the hit ratio, which equals 50%, 51%, 52%, 53%, 54%, 55%, 56%, 58% or 60% for different models) from each individual investment signal. The simulations in the figure were made using the standard normal cumulative distribution function Φ and the inverse of the normal cumulative distribution function Φ^{-1}. Each point in the figure corresponds to the value of the function $\Phi(\Phi^{-1}(H,0,1) * \sqrt{N})$, where H is the hit ratio of the model and N is the number of uncorrelated investment positions taken.
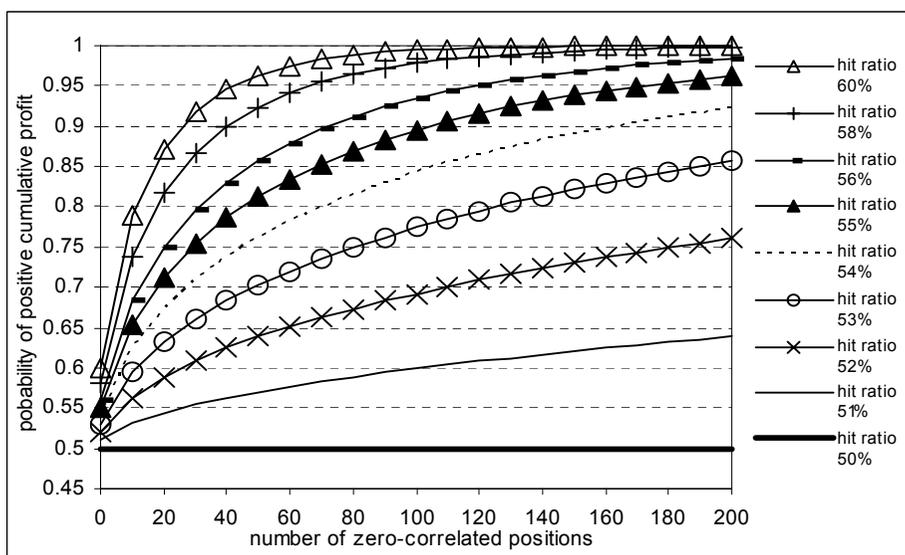
Figure 2. The probability of achieving positive total excess return as a function of the number of independent investment positions and their hit ratios.

It can be implied from the figure that diversification raises the probability of having a positive cumulative return relatively rapidly. For example, a very high (95%) probability of having a positive cumulative return can be achieved with at least 40 independent investment positions if each of the positions has a 60% probability of yielding a positive excess return or with at least 180 investment positions if each of the positions has a 55% probability of yielding a positive

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[19] A similar analysis is presented in an article by the Central Bank of Norway (Norges Bank 2004) outlining the bank's active management strategy.

excess return. Similar analyses can be carried out using the information ratios of different strategies. For example, combining 12 strategies where each of them has an individual information ratio of 0.5 (roughly a top-quartile performance) raises the information ratio of the entire portfolio to 1.75, if the strategies have zero correlation (Collins *et al.* 2005, p 91).

The main implication of the law of active management for active investing is the importance of diversification. The idea that even if individual directional forecasts rarely beat random forecasts, there can still be a minute amount of added value when we use a pool of forecasts, is shown for example, by Greer (2003). Because global bond and currency markets are highly efficient, it is relatively difficult to improve the performance of any single investment model. Furthermore, out of many active investment strategies and approaches available no single approach has been right and profitable all of the time. Therefore, in trying to achieve better performance with active management, it is important to increase N by adding more independent investment decisions [models] with a positive performance expectation; i.e., diversification.

In international currency and bond markets active investment positions can be taken and the excess return of the entire active investment portfolio diversified using different risk classes; for example, currency risk, yield curve risk, duration risk, credit risk and cross-country yield spread risk. In all of those risk classes different investment positions can be initiated in different countries, currencies and/or yield curve sectors independently, hedging the risk from other risk classes.

Further diversification of investment results can be achieved with the use of different investment styles. For example, the experience of Deutsche Bank shows that when a successful subjective fundamental investment approach is combined with a successful rule-based quantitative approach, the resulting portfolio can be superior to either approach alone (Collins *et al.* 2005, pp 33–34).

1.1.5. Overview of the different possibilities for portfolio combination

In order to combine estimated models into one investment portfolio, first the size of the capital (risk) for each individual model and position must be determined. There are several ways of doing that starting from the traditional portfolio theory and ending with more recent developments like the leptokurtic portfolio theory.

The traditional portfolio theory has been widely used in financial markets since the seminal work of H. M. Markowitz (Markowitz 1952). According to the theory, we can calculate the expected return and volatility of the investment portfolio as:

$$R_p = \sum_{i=1}^{n} w_i R_i \qquad (2)$$

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j r_{i,j} \qquad (3)$$

$$\sum_{i=1}^{n} w_i = 1 \qquad (4)$$

where: n represents the number of securities in the portfolio;
   w_i is the weight of i-th security in the portfolio;
   R_p is the expected return of the entire portfolio;
   R_i is the expected return of the i-th security;
   σ_p is the standard deviation of the return of the entire portfolio;
   σ_i is the standard deviation of the return of the i-th security and
   $r_{i,j}$ is the correlation coefficient between the returns of the i-th and j-th securities.

Although this theory has been mostly used in constructing portfolios of different financial instruments, we can also apply this theory when constructing a diversified portfolio of different investment models as developed in this thesis. In that case, R_i would represent the average monthly excess return of each individual model and σ_i the standard deviation of excess returns of each individual model.

In that case our goal would be to find the weights for each model so that the overall risk-adjusted performance of the entire portfolio of investment models would be maximized. To measure the risk-adjusted performance we can use the Sharpe ratio (Sharpe 1994), which measures the risk-adjusted excess return of any given investment fund using the excess return of the fund over the risk-free rate divided by the standard deviation of the excess return. As in the models described in this thesis, the positions are taken using derivative instruments, the results are already excess returns, and the deduction of risk-free performance is not needed. The "investment fund" used in Sharpe's paper would be in our analysis any given portfolio of active investment models with a given set of w_i's.

Mathematically our goal can be expressed in the following way: to find out the set of w_i-s so that the Sharpe ratio (S):

$$\text{Max:}\, S = \frac{R_p}{\sigma_p} \qquad (5)$$

of the entire portfolio would be maximized. There are two possibilities of finding w_i-s: through simulation or through mathematical calculations. Using simulations we can simulate different w_i-s (it would be reasonable to restrict $0 < w_i < 1$ for all i-s) and finally choose the one yielding the highest S. Alternatively, we can use an equation presented by Sorensen *et al.* (2004):

$$\frac{w_i}{w_j} = \frac{IC_i, t\sigma_j^2 - IC_{j,t}\sigma_j\sigma_i}{IC_{j,t}\sigma_i^2 - IC_i, t\sigma_j\sigma_i} \tag{6}$$

where w_i and w_j are the relative weights of models i and j and IC_i and IC_j are information coefficients of models i and j in time period t. After finding the relative weights, the actual weights summing up to 1 can be found using simple algebra.

According to more recent research (Kitt 2005), traditional portfolio theory as described above may not be the best tool to use, because it assumes that the returns of financial variables have a Gaussian distribution. In the real world, many studies (for quotations on some earlier papers see Mandelbrot 1963, pp 394–395) have found that large-amplitude deviations from mean returns occur in financial markets more often than forecasted by the Gaussian distribution. Therefore, investors may not be more interested in minimizing the standard deviation of the returns for a given return goal, but in minimizing the risk of a drawdown[20]. To do this the risk components of the portfolio are separated as fluctuation risk (variability of the returns up to a certain threshold or "noise kernel") and drawdown risk (measured as the minimum variance outside the noise kernel) (Kitt and Kalda 2006, p 141). The portfolio that has a minimum drawdown risk for a given return level is optimal for drawdown-averse investors. The fluctuation risk is not considered in this case, as it has less importance for a drawdown-adverse investor than the drawdown risk. To calculate the drawdown risk or the portfolio variance outside the noise kernel, non-kernel covariations must be used in equations 3 and 6 (see Kitt 2005, p 40 and Kitt and Kalda 2006, p 142–145).

For the purposes of this thesis the leptokurtic portfolio theory can be applied in the following way. First, the time series of excess returns from each model should be filtered and the observations (months), when the excess returns of all models are within θ standard deviations from their average monthly excess returns, excluded from the calculation of weights. After that σ_i, σ_j, $r_{i,j}$ and finally σ_p can be calculated based only on the data of those months when 1 or more models showed extraordinary excess returns (excess returns that were more than θ standard deviations from the given model's average monthly excess return). The final goal (to set w_i's so that the Sharpe ratio would be maximized) remains the same. The value of θ can be chosen to be 3 standard deviations, which was the value also used in a paper by Kitt and Kalda (2006, p 145).

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[20] Performance below certain threshold.

1.2. The overview of different possibilities for receiving investment signals

One can distinguish between two major investment styles – discretionary (qualitative) investing and systematic rule-based (quantitative) investing. Discretionary investing relies mainly on subjective judgment based on non-quantifiable information about the state of the economy and the financial markets (www.investopedia.com). It necessarily involves a certain degree of subjectivity as it is based on the opinion of an investor regarding future market dynamics. By contrast, systematic rule-based investing relies exclusively on quantitative analysis and attempts to quantify market behavior in relation to the factors which are supposed to influence it. Systematic investing in its pure form means that investment decisions depend 100% on entry and exit signals generated by quantitative investment models based on parameters validated by historical testing using quantifiable data (Gallwas 2001).

Both the discretionary and systematic approach can use a variety of inputs (factors), which can be classified into two main classes. The first of them consists of different technical factors, which are derived from the past and observable price and volume dynamics of the same financial instrument that is being traded such as trend direction, momentum, volatility, different support and resistance levels, etc. (Newman *et al* 1992, pp 435–436 and www.investopedia.com). The main advantages of this class of inputs are their timely availability and the fact that actual market movements reflect the changes in all factors influencing the supply and demand in the markets, including the ones that are not directly observable, like emotions, herd behavior and others.

The second class of inputs consists of different fundamental or economic factors such as CPI, economic activity, investment flows, relationships with other markets, companies' financial data in the case of stock and credit analysis, etc., that drive the supply and demand of certain financial instruments. Their main advantage is their usually sound theoretical base and the possibility of forecasting the changes in supply and demand conditions in contrast to just observing past changes in supply and demand that is possible with technical inputs. At the same time, these forecasts are not easy to make because of the relatively long publication lags of fundamental data and the uncertainty about possible factors that influence supply and demand in any given time frame.

In practical investing both investment styles (discretionary and systematic) and both sets of inputs (technical and fundamental) are widely used. Combining these two investment styles and two classes of inputs gives us four possibilities for receiving investment signals as presented in Figure 3 (Darnell *et al.* 2003, p 6). Investment decisions can be based on quantitative models using only price data (quadrant I), on quantitative models that also use exogenous economic variables (quadrant II), on the qualitative analysis of the economic environment

(quadrant III) or on the subjective judgment of various price graphs (quadrant IV). The most important strengths and weaknesses of each investment style and inputs are summarized in Table 1.
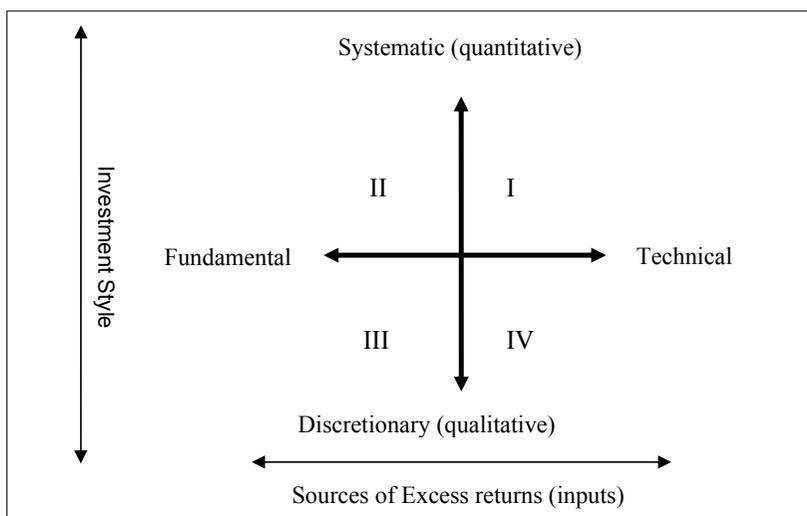
Figure 3. Graphical overview of the different possibilities for receiving investment signals

Table 1. The most important strengths and weaknesses of different investment styles and inputs (sources: Gallwas 2001, Darnell *et al.* 2003 and www.investopedia.com, compiled by the author)

Style or input	Strength	Weakness
Systematic	Eliminates emotional factors and related common mistakes. Investment decisions are consistent over time. Risk management can be based on simulated historical performance.	Does not take into account sudden important factors such as political events, terrorist attacks, hurricanes, etc. Easy to over-optimize, leading to data mining bias and spurious results.
Discretionary	Flexibility in selecting important information, including unquantifiable information such as political events, terrorist attacks, hurricanes, etc.	Different (and often conflicting) ideas, beliefs and analyses can lead to lagging investment decisions as it is difficult to achieve a consensus between decision-makers. Human emotion can cause investors to be inconsistent and undisciplined.

Style or input	Strength	Weakness
Technical inputs	Timely available. Can also capture factors not directly observable or measurable (like emotions, herd behavior, etc.)	Do not capture economic factors. Easy to over-optimize, leading to data mining bias and spurious results.
Fundamental inputs	Can capture a wide variety of possible factors that can influence markets. Less threat of over-optimization as inputs usually have theoretical reasoning.	Often published with significant lags.

As a general rule, the quantitative approach tends to work better in trending environments, especially when the trends are connected to macroeconomic fundamentals (business cycles, etc). The subjective (judgmental) approach tends to work better in volatile or mean reverting environments and it may also be better when an investor has a medium to long term scenario that could translate into event risk (Collins et al. 2005, p 78). The popularity of the systematic approach has been steadily growing with systematic traders outnumbering discretionary traders by about three to one already in the 2nd half of 1990s (Cavaletti 1997).

Based on the database of Barclay Trading Group (2005), the average yearly performance of 83 monitored discretionary CTAs between 1987–2003 was 10.12%, with an annualized Sharpe ratio[21] of 0.57 and the average yearly performance of 354 systematic CTAs was 11.50% with an annualized Sharpe ratio of 0.43. The t-statistic to test if the corresponding average yearly performances are different has a value of 0.57 with the test having 183 degrees of freedom. The results show that there is no systematic difference in the long-term performance of different investment styles over the long run. This means that the performance of an investment manager depends more on the level of his or her skills and not so much on the investment style chosen.

The main shortcoming of fundamental data, namely the often very long publication lag, can sometimes be reduced with timely available proxies from the financial markets. For example, one can use the timely available spot prices of traded commodities as a proxy for future inflation. Commodity prices are also related to capital flows to and from commodity exporting/importing countries in the future, leading this way to changes in exchange rates. One can use stock prices as a proxy for expected economic activity and interest rates in

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[21] The annualized ratio of average excess return to volatility, calculated as $\sqrt{n}$ * (average excess return in period)/(standard deviation of average excess return in period), where n is the number of periods in a year, see Sharpe (1994).

bond markets can give an indication of the future borrowing costs of enterprises, leading to changes in profit levels and stock prices. Such an approach, where movements in one market are modeled as a function of price movements in other markets, is called "intermarket analysis" (see Murphy 2004) and has to be carried out with great care, because there is a high threat of estimating spurious regressions when the relationships between different markets are tested without a sound theoretical base.

Although it is possible to combine the two styles of investing (systematic and discretionary) in various degrees, usually for one investment strategy one style is dominant. The benefits of diversification can be best achieved by dividing investment funds and/or risk limits between investment managers who apply different investment styles. For example, such an approach has been implemented in the Central Bank of Estonia (see Vesilind and Kuus 2005, p 13) where a three-level diversification strategy is being used: the first level divides investment decisions between external and internal managers, the second level between discretionary and systematic styles, and the third level between different investment models within a systematic approach.

This thesis focuses only on the systematic investment style based on quantitative models (quadrants I and II), because for these models the expected return and risk statistics can be calculated from historical tests. The investment results that can be achieved with models described in the thesis can be further improved by adding managers who follow a discretionary investment style.[22]

Systematic investing is most suitable in markets that are sufficiently liquid, standardized, developed and have less event risk. For example, the fixed income markets of government debt of developed countries lend themselves to the use of quantitative techniques more than other fixed income classes (like, for example, the debt of low-rated companies or the government debt of low-rated developing and/or emerging economies) (SSGA 2003, p 1).

The systematic (quantitative) analysis of financial markets is by no means a new field of analysis: some earlier works on the mechanical trading of commodity derivatives date back to the 1930s (for example, Gann 1934) and a wider spread of systematic analysis started in the 1970s with the help of computers (for example, Appel 1974). Over the years, a number of models have been developed to analyze and predict market behavior; their number and degree of sophistication continues to grow. It is impossible to count all the quantitative techniques which have been used for that purpose – from simple moving averages in technical analysis to neural networks and genetic algorithms.

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[22] Diversification can be even further improved by hiring external managers whose performance results are lowly correlated. Research (Vesilind and Kuus 2005, p. 25) shows that in some cases low correlation between performance results can be achieved even in cases when both in-house and external managers use mostly the same investment style.

In spite of their large amount and wide spectrum, the quantitative techniques used can still be divided into three major categories: "fair value" models, investment models based only on the price data of the same traded instrument and investment models that also use economic (fundamental) inputs.[23] For the purpose of this thesis the category of quantitative fundamental models can be further divided into two sub-categories: quantitative fundamental investment models for taking foreign exchange risk and quantitative fundamental investment models for taking interest rate risk.

1.3. Quantitative "fair value" models and models based on past price data

1.3.1. Quantitative "fair value" models

Quantitative "fair value" models are mostly used to explain the past behavior of a particular financial market on the basis of several macroeconomic indicators as inputs. The purpose of such models is often not to predict market behavior, but rather to assess whether the price of a security is close to the estimated "fair value." The macroeconomic indicators that have the biggest impact on interest rates are the producer price index (PPI), consumer price index (CPI) and gross domestic product (GDP) (Lien 2006, p 11). One of the most well-known and acknowledged examples of such a model for interest rate levels using the abovementioned indicators is the "Taylor rule" (Taylor 1993), which is used to explain monetary policy interest rate dynamics by output gap and inflation dynamics. Other examples are the Goldman Sachs World Interest Rate Equilibrium model (GSWIRE) for 30-year U.S. Treasury bond yield (Hatzius 1999), a term structure model of government bond yields by Diebold *et al.* (2002), and many others.

For foreign exchange markets one of the most commonly used long-term determinants is the purchasing power parity (PPP) (Rosenberg and Folkerts-Landau 2002, p 32–41), which is built on the notion of arbitrage across all tradable goods and services. Other macroeconomic determinants that have medium-to-long-run effects are the terms of trade changes (especially for commodity-oriented industrial economies), current account (im)balances and net international investment positions, fiscal and monetary policy (following the framework of the Mundell-Fleming model), money supply and trends in productivity and investments (Rosenberg and Folkerts-Landau 2002, pp 42–62 and 96–99). Examples of long-term models for exchange rates based on PPP

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[23] Fundamental inputs can be used either in the form of macroeconomic data (pure fundamental models) or in the form of timely available proxies from other financial markets (intermarket fundamental models).

and/or other abovementioned determinants can be found in an OECD study about the equilibrium exchange rate of the euro (Koen *et al.* 2001, p 26) and other papers (Rapach and Wohar 2002, Apte *et al.* 2002, Norfield 2004, etc).

The easiest way to construct "fair value" models is simple regression analysis. More complex "fair value" models have also been developed that also include expectations and model "learning" using a Kalman filter, genetic algorithms, neural networks or other methods. Examples of such models are a model for the trading of US T-bonds and T-notes by Benzschawel and Dzeng (2001) and the USD/SAR model by Basdevant *et al*.(2001).

In addition, the author of this thesis has developed fair value models for major government bond yields and exchange rates (see Vesilind 2003). As a baseline for modeling interest rate and yield curve spreads, the author used a conventional IS-LM framework, and for modeling exchange rates, the standard monetary model of exchange rates. The estimated models covered 10-year government bond interest rate levels and 2-year–10-year yield curve spreads in the USA and Germany, and the USD/EUR and USD/JPY exchange rates. The results indicated that the fundamental indicators can give relatively accurate estimates of the equilibrium value *ex post*, but the *ex ante* model's estimates may lag behind the actual market cycle's turning points.

It has been observed that the markets can deviate from their theoretical "fair values" for a considerable period of time. The methodology to answer the question, 'How long can exchange rates deviate from their fundamental equilibrium?' and whether fundamental "equilibrium" can be used for trading exchange rates, is proposed in a paper by R. Darnell and R. Arnott (Darnell and Arnott 1997). In the paper the authors divide the future exchange rate movements into two sub-periods: a short-term period where the random variance around the fundamental equilibrium is larger than the cumulative effect of fundamental factors and a long-term period where the variance due to fundamental factors is larger.

The length of the "short-term" varies in different studies. The length of the exchange rate adjustment from its "fair value" calculated using PPP is elaborated in MacDonald (1999). He finds that the half-lives of bilateral exchange rate adjustments from PPP levels are as long as 3 to 4 years (*ibid*, p 689). It has also been found that macroeconomic variables have a stronger effect during extraordinary circumstances such as hyperinflations and remarkably little effect under more stable times (Frankel and Rose 1995, p 1709).

Another shortcoming of "fair value" models is that in spite of providing useful indications of the "fair value" of certain financial instrument, they are rarely directly applicable to active investing alone because they do not usually

give concrete information about when to enter or exit the market.[24] If we want to rely solely on quantitative signals without human subjectivity, then the model has to go beyond merely predicting a price change and/or a "fair value" – it must also decide if and at what time a certain action has to be taken (Gencay *et al.* 2003, p 912).

Although the importance of changes in different economic indicators to changes in exchange rates and interest rates has been found to be statistically significant in many studies, extracting concrete trading signals from economic models and implementing them is not easy, because the markets react to economic news relatively quickly making it difficult to profit from the changes in economic fundamentals. Studies have shown (for example, Lien 2006, p 58) that the majority of daily market movements after the release of an important economic indicator happen within the first 20 minutes after the release. In addition, the relative importance of different economic inputs changes over time: for example, while the most important driver of foreign exchange rates in 1992 was the trade balance, in 1997 it was the amount of unemployment (*ibid,* p 60).

Furthermore, the models that include learning behavior have the same shortcoming as technical price models; namely, there is a high risk of over-optimization due to extensive data mining, resulting in good "learned" relationships from the past data that may sharply lose their predicting ability outside the estimation period. Also, it has been estimated that currently (as of June 2005) six major currencies are all being traded in close approximation of their fair value (Collins *et al.* 2005, pp 11–12), which makes the profitable use of fair-value models at this time even more questionable.

1.3.2. Quantitative investment models based on price data

Past price data can be used for forecasting market movements in pure technical models in the form of different technical indicators (different moving averages, relative strength indicators, support and resistance levels, and many others) but also in different econometric models using trend, seasonality, ARMA (auto-regressive moving average) components and other factors. In both cases the data used as an input for calculating trading signals is endogenous – opposite from fundamental investment models that also use exogenous data.

The theoretical reasoning for the tools of technical analysis to work lies in the hypothesis of asymmetric information (Reitz 2006, pp 121−123). If news is not instantaneously available to all market participants, uninformed traders may infer a signal from analyzing the changes (that resulted from transactions

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[24] With some exceptions. For example, Giacomelli and Li (2002) successfully add survival analysis to fair value models to get concrete trading signals based on the duration the currency has deviated from its fair value.

initiated by informed traders) in asset prices. In this way technical trading rules can be interpreted as a cheap proxy of Bayesian learning (*ibid*, p 135). The profitability of technical trading rules has also been explained with the presence of herd behavior among investors (Banarjee 1992).

The number of pure technical models has grown especially fast during the last decade with the advent of computerized analysis of financial markets and the development of special trading strategy back-testing software (like Tradestation, Metastock, etc.). A large share of technical investment models is trend-following in nature and technical analysis is especially popular among currency managers: studies have estimated that about 62.5% of currency CTAs are of a purely trend-following nature with an additional 12.5% using a trend-following style together with fundamental inputs (Middleton 2005, p 16).

For trend-following models to work, the upswings and downswings in the markets have to be large and frequent enough to cover the losses that these models usually generate during the periods when the markets are trading within a range. Trend-following models take mainly medium- to long-term positions. The reason for that may lie in the results of research, which shows that financial time series tend to move randomly on a daily basis, but are positively serially correlated when viewed on a longer (for example, monthly) basis (for corresponding tests on exchange rates see Rosenberg and Folkerts-Landau 2002, p 20).

The existence of positive serial correlation and trends in market prices reflects the existence of "herd behavior" among investors. The market often gets accustomed to the underlying trend in a long cycle and at the end tends to shrug off any adverse underlying fundamental developments as being just a temporary phenomenon (Rosenberg and Folkerts-Landau 2002, p 61). Therefore, existing trends can last in spite of turning fundamental factors as long as investors recognize that the change in the fundamentals is permanent. Research has also found that technical trend-following trading rules are more efficient at predicting exchange rate changes on days when central banks intervene and that their profitability is much lower if intervention days are removed from the sample (LeBaron 1999 and Saacke 2002).

An example of a simple trend-following technical model is the moving average crossover strategy that is monitored in a portfolio of currencies in Deutsche Bank (Deutsche Bank 2002, p 12). The average annual excess return of this strategy during 1986–2002 was between 2.2%–9.6% with an annualized Sharpe ratio of between 0.35–0.86, depending on the currency pair. A description of a simple moving average crossover strategy is also presented in JP Morgan's FX & Commodity barometer (Normand *et al.* 2004, p 8–9) It was additionally tested in a study by Collins *et al.* (2005, p 78). A paper by Bianchi *et al.* (2004) quotes several more papers that have reported excess returns in foreign exchange markets using rules based on moving average filters.

Moving average trading rules tend to generate more losing trades than winning trades, which in itself does not pose a problem as the average profit from winning trades usually exceeds the average loss from losing trades by a fairly large margin. For example, the study by Rosenberg and Folkerts-Landau (Rosenberg and Folkerts-Landau 2002, p 17) shows that depending on the currency pair, average profit from a winning moving average trade was between 2.0% and 5.92%, while the average loss from a losing trade was between –0.62% and –1.72%[25]. A negative aspect is that moving average trading rules can have quite significant maximum cumulative losses (drawdowns) during non-trending periods. For example, the study by Collins *et al.* (2005, p 78) found that the maximum drawdown using 32, 61 and 116-day moving averages was between –16.6% and –34.4%, depending on the currency pair.

A wide range (over 200) of more complex technical models are monitored continuously by an independent organization, Futures Truth Inc., and the results are reported monthly in "Futures Truth Magazine". Some examples of the systems, that have been tested also in the IR and FX markets covered in this thesis are (return statistics are from "Futures Truth" 5/2005, pp 12–31 as of September 30, 2005):

- Fusion (Strategic Trading…). One of the newest systems that is also being tested on USD/JPY and USD/CHF exchange rate futures and US 10-year government bond futures. Monitored in "Futures Truth" since December, 2004. Annualized return[26] of 146.4% on USD/CHF exchange rate futures, 16.7% on USD/JPY exchange rate futures and –96.9% on US 10-year government bond futures.

- Trendchannel (Trendchannel …). One of the oldest and simplest technical systems still working in the market. Tested on USD/JPY and USD/EUR exchange rate futures and on US 10-year government bond futures. Annualized return of 58.9% for USD/JPY exchange rate since 06/98, 115.6% for USD/EUR exchange rate since 12/98 and 53.8% for US 10-year government bond futures since 06/98.

- Dollar Trader (Dollar Trader …) for Currencies. One of the oldest and best performing systems monitored on USD/EUR and USD/JPY exchange rate futures. Annualized return of 127.4% for USD/EUR exchange rate futures since 01/99 and 130.6% for USD/JPY futures since 01/96.

- Lil Gapper. One of the oldest and the worst performing system monitored. Tested on USD/GBP, USD/JPY and USD/CHF exchange rate futures with an annualized performance of –307.9%, –162.2% and –264.6%, respectively, since 01/91.

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[25] The test covered DEM, JPY, GBP CAD, AUD, NZD and CHF exchange rates against USD from January 1986 to April 2002.

[26] Based on having the minimum capital required to trade in the system effectively.

Along with the technical models monitored in "Futures Truth Magazine," we can also find these models in academic literature. Some examples:

- Trend-following trading model developed by R. Gencay *et al.* (Gencay *et al.* 2003, p 913) uses specially weighted moving averages, over-bought/oversold contrarian behavior in the case of extreme movements and a trailing stop. Model was applied to USD/DEM, USD/CHF, USD/FRF and DEM/JPY exchange rates between January 1, 1990 and December 31, 1996 and achieved an average annual excess return of between 3.66% and 9.63%, depending on currency pair (with all costs deducted).

- Technical trading rules developed by Neely *et al.* (1997) use the genetic programming approach and find strong evidence of economically significant out-of-sample excess returns for six currency pairs: DEM/JPY, USD/DEM, USD/CHF, GBP/CHF, USD/JPY and USD/GBP over the period 1981–1995.

- In addition, an article by S. Reitz (2006, pp 1–3) has a wide range of citations to different articles describing the profitability of moving average trading rules and other technical indicators.

The main shortcoming of pure technical models is that their development is usually based on the simulations of different strategies and parameter values. Even if such simulations are carried out strictly *ex-ante*, the possibly very large simulation numbers can reduce the degrees of freedom of the model significantly. This means that the trading strategy that works well during both the simulation (estimation) period and *ex ante* test period may do so only because of chance and not because of its predictive capabilities. Therefore, there is a high risk that such models can lose their well-reported simulated performance after actual implementation.

Econometric models have a somewhat different approach compared to pure technical models, in many cases enabling more flexibility. At the same time the main caveats (mostly the threat of over-fitting; i.e., the threat of using too many parameters and/or running too many different simulations) remain the same. For example, a description of the application of simple AR(I)MA models to exchange rate forecasting can be found in a paper by M. K. Tambi (2005). In his paper he successfully develops forecasting models for the INR exchange rate against the SDR, GBP, EUR and JPY, but fails in developing a model for INR/USD. We can also find descriptions of AR(I)MA models in papers where they are used as a benchmark for evaluating the performance of more complex models. For example, Kamruzamman and Sarker (2003) use ARIMA models as benchmarks for evaluating the performance of Artificial Neural Network models in forecasting exchange rates and Bhardwaj and Swanson (2006) use AR, ARMA, random walk and GARCH models as a benchmark for evaluating the performance of ARFIMA models.

Fiess and MacDonald (1999) use multivariate cointegration methods to exploit the structural relationships between high, low and close prices in exchange rates. They test the approach on USD/DEM and USD/JPY exchange rates from August 1986 to August 1996 and find that the models produce a credible out-of-sample forecasting performance in terms of beating a martingale even after accounting for risk and transaction costs. In addition, GARCH volatility equations have been successfully used in drawing volatility bands and using these bands for intraday trading (Tivegna 2003).

Various seasonal patters in the markets can be studied separately, or alternatively seasonal factors can be incorporated into econometric models. An example of a study on seasonal patterns in the prices of U.S., German and Japanese 10-year government bond futures is a master thesis by Triin Kriisa (2005). In her thesis she found that the prices of U.S., German and Japanese 10-year government bond futures have identifiable seasonal movements. The prices of all three futures tend to appreciate more than average in September and decline in March (U.S. and German futures), in November (U.S. futures) and in June (Japanese futures). However. the study did not mention nor investigate any theoretical reasons that could explain such seasonal movements.

From the model overviews given above, we can conclude that technical analysis is widely used in financial markets and the number of different approaches available for model-building is very large. In order to include all the basic approaches into a portfolio of models at least two models have to be tested – one based on technical analysis and the other based on econometric analysis. In order to avoid over-fitting and to achieve higher robustness, the model using technical analysis has to be as simple as possible and not include any optimized parameters. A daily model based on the moving average crossover strategy that has two moving averages with fixed lengths fulfills the criteria set above well. The lengths of the moving averages can be, for example, 5 and 50 business days (i.e., 1 week and 2 months). Another model would then use econometric techniques together with seasonal factors. An ARMA model with seasonal dummies seems to be a suitable choice here if we choose to keep the models simple and avoid more complex approaches like the multivariate cointegration methods used by Fiess and MacDonald (1999).

1.4. Quantitative investment models for taking foreign exchange risk

1.4.1. The framework for analyzing possible inputs for quantitative fundamental investment models for taking foreign exchange risk

As it was previously mentioned, the "fair value" models are rarely directly applicable to active investing, because they do not give concrete signals for

action. In order to base investment decisions on quantitative economic signals, the models developed must also decide if and at what time a certain action (to buy some asset at a specified time and/or price) has to be taken. In this thesis such models are called "quantitative investment models."

Previously developed investment models in foreign exchange markets use mostly short and medium term determinants of exchange rates as inputs, leaving long-term determinants (such as PPP, productivity trends, etc.) for "fair value" models.[27] The wide range of quantitative investment models for FX market with economic inputs can be best described using the framework proposed by Normand *et al.* (2004, p 3), where the factors influencing the foreign exchange market are grouped in four main categories:

- economic variables influencing the capital flows between countries
- technical price trends
- capital flows of large international investors
- investors' positions and sentiment.

The capital flows between countries are reflected in the balance of payments: a negative (positive) balance of payments number indicates that capital is leaving (entering) the economy at more rapid rate than it is entering (leaving), and hence, theoretically, the home currency should fall (rise) in value (Lien 2006, p 37). There are two main accounts in the balance of payments: the financial account and the current account.

The flows that are reflected in the financial account are determined mostly by the tendency of the capital to move to countries where its (expected) risk-adjusted return is higher. The return can be measured by economic growth (either past or expected/forecasted), return in debt markets (short-term interest rates as a measure of current yield and longer-term swap rates as a measure of expected future yield) and/or return in equity markets (Normand *et al.* 2004, pp 4–8). The risk associated with (expected) investment return can be measured using various indicators that can be grouped into two sub-sets. The first sub-set consists of various measures of the historical volatility of the return used (i.e., interest rate or equity market return) time-series (*ibid*). The other sub-set consists of various external indicators. For example, the Deutsche Bank Risk Appetite index consists of the following components (Rosenberg and Folkerts-Landau 2002, p 29):

- G3 (the USA, Eurozone and Japan) implied three-month FX volatility;
- VIX index (measures expected volatility in the S&P 100 index based on option prices traded on the Chicago exchange);

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[27] However, some attempts to use the changes in PPP for concrete trading signals have also been made (for example, see Collins *et al.* 2005, p 79-81), but the results have been weaker compared to models with more short-term determinants with information ratios mostly below 0.5.

- U.S. High Yield Bond Spread,
- JP Morgan's EMBI+[28] composite index
- Journal of Commerce Metals index and
- G3 yield curve spread between 10-year government bond and cash interest rates.

The dynamics of major movements in the current account are often related to the changes in trade flows and to the changes in the prices of major traded goods. A sharp increase in the price of some major import (export) article can cause a sharp increase in the outflow (inflow) of capital, which in turn has a direct effect on the exchange rate of the domestic and other connected currencies. Raw materials and commodities can serve as good examples here, as they make up a big share of many countries' trade flows. For example, the increase of the price of oil from 11 dollars a barrel in 1999 to over 70 dollars a barrel in 2006 sharply increased the capital inflows from oil-importing countries to oil-exporting Middle Eastern countries. While most of these countries have exchange rates pegged to the US dollar, the increase in oil prices resulted in an accumulation of foreign exchange reserves. These were in turn invested mostly into US assets. The calculations made in Deutsche Bank (Chadha 2006, p 15) indicate that the capital flows from the Euro area countries and Japan (big oil-importing regions) through Middle Eastern countries (big oil-exporting countries) to U.S. assets amounted to 50 billion dollars in 2004 and 95 billion dollars in 2005, translating to 4% and 8% "first round" support effects for the U.S. dollar in the given years *ceteris paribus*. Another example is the relationship between gold prices and Australian dollar/U.S. dollar exchange rate. Australia is the world's third largest producer of gold, exporting about $5 billion worth of the precious metal annually. Therefore, the rise in the price of gold causes the importers of gold to demand more Australian currency to cover higher costs, resulting in very strong correlation (0.8) between these two time series (Lien 2006, pp 148–149).[29]

The size of the current account deficit has been also used as a risk indicator measure in order to determine the flows reflected in the financial account (Rosenberg and Folkerts-Landau 2002, p 29).

The second set of indicators is based on the fact that the markets can trend for long periods of time even if the trends do not coincide with observable changes in economic fundamentals. The rationale for including this set of indicators can be found in the previous chapter where the models based only on past market data were discussed.

The third set of indicators assumes that large actual FX transactions can reflect that some big investor has important information that is not yet known to

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[28] Emerging Market's Bond Index
[29] Australia is a big exporter of other industrial commodities as well, which has also led to high correlations between AUD and other commodity prices besides gold.

other market participants. In addition, large FX transactions can move the markets themselves because they change the supply–demand relationship (Normand *et al.* 2004, p 9). A study by Sager and Taylor (Collins *et al.* 2005, p 55) finds that as most real money managers and larger hedge funds do not want to perturb the market with sudden large-size transactions, then they adjust their portfolios and positions gradually after new significant data innovations. Therefore, first order flows of large, active, and informed customers are usually only small parts of the total large portfolio shifts being executed and these flows usually indicate that similar orders are likely to be fed into the market in near future. If the market does not absorb the first orders easily, then it may lead to significant price changes when the remaining orders are executed.

According to a survey by Gehrig and Menkhoff (2002), flow analysis is the most important source of information for FX dealers (26.2% of respondents viewed it as their most important source of information), while its importance among fund managers is smaller (only 16.8% of fund managers viewed flow analysis as their most important source of information). Flow analysis provides valuable information mostly for shorter time horizons: 25.4% of survey respondents viewed it as useful in intraday analysis and 37.3% of respondents viewed it as useful in forecasting market movements up to a few days ahead (*ibid*).

The flows of different market players have different importance for different exchange rates. Research by R. K. Lyons (2001) showed that the FX order flows of non-financial corporations have no statistically significant positive effect on euro or Japanese yen exchange rates. At the same time FX order flows of un-leveraged real-money financial accounts have a highly significant positive effect on the euro exchange rate and FX order flows of leveraged hedge funds on the yen exchange rate (*ibid*). The effect of FX order flows is mostly con-temporaneous and not leading: while a study by Deutsche Bank (Rosenberg and Folkerts-Landau 2002, p 26) found a statistically significant relationship between euro, yen and U.S. dollar exchange rates and FX order flows in contemporaneous regressions, the relationship became statistically insignificant when one-week lagged FX order flows were used.

The data on investor's positions (the fourth set of indicators) is mostly available only to big international investment banks who can monitor their clients' cash flows and positions; for example, Deutsche Bank's Flow Indicator (Deutsche Bank 2002, p 25) and JP Morgan's proprietary Flow of Funds database (Normand *et al.* 2004, p 3). At the same time there also exist publicly available indexes; for example, the IMM Commitment of Traders Report[30] (Deutsche Bank 2002, p 25), the Consensus Bullish Sentiment Index of Market Opinion (Con-

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[30] Shows the number of long and short positions in international money markets.

sensus) and indexes available to clients of financial corporations, such as the Russell Mellon Fixed Income Investor Survey[31] (www.workbench.mellon.com).

This kind of data gives two sets of valuable information to market participants: it reflects the tendency of FX markets to return from extreme levels back to historical averages (Rosenberg and Folkerts-Landau 2002, pp 9–11) and it can give an indication of possible stronger support- and resistance levels and possible price levels where major breakouts can occur (Collins *et al.* 2005, p 55). The data can be extracted in various ways from directly observed positions and orders of the clients to the more widely available price data of options. For example, the put and call prices of the currency options (namely, the differences between the implied volatilities of the two far out-of-the money options with the same expiration and strike price) can be used to gauge information about investors sentiment and the direction of perceived risk (Deutsche Bank 2002, p 25 and Lien 2006, p 156), although other studies have found (Cooper and Talbot 1999, p 70) that implied forward volatility curves calculated from options' prices have not correctly forecasted sudden changes in the volatilities of exchange rates.

Along with the factors described in the paper by JP Morgan (Normand *et al.* 2004) additional unexpected factors can be important movers of exchange rates. These factors include the actions (interventions) of central banks, statements of policy makers and other unexpected news. The interventions of central banks usually smooth directional changes in exchange rates and create serial correlation in exchange rate movements (Darnell *et al.* 1997, p 8). At the same time the interventions of central banks are not usually successful in influencing the longer-time trends in exchange rates[32] because of the huge size of the forex market (average daily turnover $ 1.9 trillion in 2004 (BIS 2005, p 9)) and the limited amounts of central bank reserves available (usually the maximum sizes of FX interventions have been up to several billions of U.S. dollars[33]) (Rosenberg and Folkerts-Landau 2002, p 124). For example, the statements of policy makers and other unexpected news are collected in a database NEWSMETRICS (Tivegna and Ghiofi 2000) and used successfully in the intraday trading of major exchange rates in a paper by M. Tivegna (2003).

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[31]   A monthly survey of 25-30 major, non-leveraged international fixed-income fund managers. The survey tracks the actual currency exposure of these funds at the end of the month in question (Deutsche Bank 2002, p 25).

[32]   However, exceptions exist. For example, when a central bank intervention acts as a "coordinating signal" and brings along other traders on the same side as the central bank (see discussion on this subject in Taylor 2005).

[33]   One of the more recent large FX interventions that also influenced the movements of the currencies under study in this thesis happened between September 2003 and March 2004, when the Bank of Japan intervened with a total amount of 244 billion dollars in to avoid yen appreciation below 100 JPY/USD (Bloomberg data, author's calculations).

There exist quantitative FX models that use only one category of previously mentioned indicators and models that also use many of them. Out of the models that use multiple inputs, there are models that weigh different inputs equally through time and models where the weights of different inputs change. There can also be several economic time-series representing one input (for example, one can use CPI, PPI, GDP deflator or even daily available exchange-traded raw material's price indexes as a proxy for inflation) and one can use many methods to extract signals from the inputs. The models can base their signals on simple directional movements of the inputs, on different forms of regression analysis or on more advanced methods and types of analysis like genetic algorithms and neural networks. References and examples are given in the next chapter.

1.4.2. Previously used practical approaches and developed investment models for taking foreign exchange risk

Below are some examples of different FX models previously developed starting with simpler single-factor models and ending with different multi-factor models:

- single-factor models based on an interest rate differential (carry)
- models that use carry together with various risk measures
- models using indicators of economic activity
- multi-factor models

The examples of the models include the framework and theoretical background of the models, as well as the performance statistics where such information was available.

The most straightforward single-factor models in FX markets use the covered and uncovered interest-rate parities that connect interest rate levels in two countries with expected and forward exchange rates. According to the covered interest-rate parity condition, an investment in a foreign-currency deposit (yielding i_f) fully hedged against exchange rate risk (costing forward discount FD) should yield exactly the same return as a comparable domestic-currency deposit (yielding i_d), since these two strategies have the same risk characteristics (Rosenberg and Folkerts-Landau 2002, p 65):

$$i_f - FD = i_d \qquad (7)$$

$$\text{or } FD = i_f - i_d \qquad (8)$$

The empirical evidence in support of the covered interest-rate parity is quite robust (*ibid*), mainly because the differences between the returns of the two abovementioned strategies can be directly profited from with no risk.

According to the uncovered interest-rate parity condition, the expected return from an uncovered foreign-currency investment (yielding i_f minus the

expected change in the exchange rate $E(\Delta e)$) should equal the expected return on a comparable domestic-currency investment (i_d) (Rosenberg and Folkerts-Landau 2002, p 65):

$$i_f - E(\Delta e) = i_d \qquad (9)$$

$$\text{or } E(\Delta e) = i_f - i_d \qquad (10)$$

In efficient markets both the covered and uncovered interest rate parities should hold and therefore, the forward exchange rate should be an unbiased predictor of the future spot rate:

$$E(\Delta e) = FD \qquad (11)$$

However, this hypothesis has not found strong support in empirical research. Based on many studies in FX markets (for example, Hansen and Hodrick 1980, Fama 1984, Bansal and Dahlquist 2000, etc.) forward exchange rates are not on average accurate predictors of future spot exchange rates. Even more: the exchange rates tend to move rather in the opposite direction than predicted by the uncovered interest rate parity. For example, a survey of 75 published papers on this subject found the average estimate of the coefficient β in the following equation:

$$E(\Delta e) = \alpha + \beta(FD) \qquad (12)$$

to be –0.88 (Rosenberg and Folkerts-Landau 2002, p 72). In addition to being statistically significantly different from 1, the value of β is negative and close to –1: it is almost the opposite of the value predicted by the uncovered interest rate parity.

This inefficiency (also referred to in economic literature as the "forward premium puzzle" and "forward discount bias") can be caused by several factors. According to the research (for example, see Normand *et al.* 2004, p 4–8 and Lien 2006, pp 136–137), the level of short term interest rates is an important determinant of capital inflows. The higher the interest rate is, the higher the potential return of capital is, and this causes an increase in capital inflows. With larger capital inflows, the domestic currency tends to appreciate as the demand for the domestic currency increases. At the same time arbitrage conditions demand the forward value of a currency with a higher domestic interest rate level to be lower than the currencies' spot value; i.e., the currency has to depreciate for the arbitrage condition to hold. Higher capital inflows due to higher interest rates may not allow the currency to depreciate as much as predicted by the arbitrage condition, supporting in this way the forward premium puzzle. For example, since the end of 2001, when the Federal Reserve of the United States started cutting the base interest rate, foreign investors began to sell U.S. assets in search of higher yields elsewhere. This resulted in an

increasing supply of U.S. dollars, causing the value of the dollar to depreciate (Lien 2006, p 36). Other explanations for the puzzle include (but are not limited to) the hypothesis that the currencies of the countries with higher short-term interest rates are riskier than the currencies of the other countries and the view that the market simply makes repeated expectational errors (Rosenberg and Folkerts-Landau 2002, p 72).

The trading based on this inefficiency can be demonstrated by a simple interest rate model (for example, see Deutsche Bank 2002, p 13), which uses the short-term return of debt markets (1-month interest rate) as the only input. The model gives a signal to buy the currencies of the countries with higher interest rates and to sell the currencies of the countries with lower interest rates. Although the idea to use such short-term interest rate differentials as an input is relatively old (the research studying this inefficiency in foreign exchange markets started already in the 1970s - 80s, see Hansen and Hodrick 1980), the models' performance has been positive up to the present time. Depending on the number of currencies traded each month (from 1 to 9 currencies on both the buy and sell side) the strategy has produced annualized excess returns of between 2.90% - 9.27%, with annualized Sharpe ratios between 0.27–1.37 (Deutsche Bank 2002, p 8). On individual currency pairs the information ratios have been between 0.25 and 1.22 (Collins *et al.* 2005, p 79).

Although historically positive, the simple carry-based models have had relatively long periods of poor performance. For example, the maximum draw-down of the different combinations in the Deutsche Bank's model described in the previous paragraph ranged from –8.87% up to –63.33% (Deutsche Bank 2002, p 10), and of the different individual currency pairs tested in a paper by Collins *et al.* (2005, p 78) from –9.5% to –45.1%. At the same time it can be observed (Rosenberg and Folkerts-Landau 2002, p 30 and Lien 2006, pp 138–141) that the performance of the carry-based models is closely linked to the movements in an index measuring investors' appetite to take on risk. Carry trades are the most profitable when investors are more willing to take on risk and unprofitable when investors are less willing to take on risk. This has led to different attempts to modify simple carry-based models with the inclusion of risk factors.

One of the first attempts in that direction was made in 2001, when the analysts in JP Morgan investment bank started testing the predictive power of the Liquidity and Credit Premium Index (LCPI) (JP Morgan 2001). This index was constructed from six indicators: the US Treasury Yield Error (the difference between on-the-run and off-the-run government bond interest rates), 10-year swap spread, EMBI+ spread, US High Yield spread, FX market volatility and Global Risk Appetite Index (Kantor and Caglayan 2002, p 1–3). Depending on the LCPI index being either in risk seeking, risk neutral or risk averse mode, traditional carry-trades are taken either in the traditional way (buying the currencies of the countries where the short-term interest rate is

higher) or the opposite way (JP Morgan 2001, p 1–3). Later, current account deficit (*ibid,* p 4) and equity market volatility (Kantor and Caglayan 2002, p 3) were also tested as inputs. Besides constructing a separate index for risk appetite, analysts in JP Morgan have also used a methodology where carry (short-term interest rate differential) is directly divided by FX market volatility as a risk factor (Gaglayan and Giacomelli 2005, p 4). The latest test results indicate that this strategy by itself has an information ratio of between 0.45 and 1.09, depending on the currency pair (test period January 1994 – June 2004, see Normand *et al.* 2004, p 21). When the strategy was combined with a risk tolerance index the average information ratio of the model rose to a level as high as 2.21 (test period 1998 – 2004, see Gaglayan and Giacomelli 2005, p 8).

Risk-adjusted carry as an input is also used in a model developed by analysts in ABN-AMRO bank (Mackel 2005). They use the differences in 3-month deposit interest rates in two countries divided by the 3-month actual volatility of the currency pair (risk-adjusted carry). The trade is initiated when the risk-adjusted carry is above its 2-year rolling average. Data is re-calculated daily. The best information ratio of the strategy occurred with the AUD/USD currency pair (1.61) in 2003–2004.

A good example of a model that uses economic growth expectations as the only input to take FX positions is the "Economic Activity Surprise Index" currency model by JP Morgan (JP Morgan 2002). This model constructs a "surprise index" based on 25 US economic activity data releases[34] and the difference between the actual data release and the previous consensus estimate. The model was tested on USD exchange rate against EUR, JPY, GBP, CHF, AUD and CAD from January 1996 to October 2001, with an information ratio, depending on the currency pair, of between 0.67 and 1.16 (*ibid*, p 1). Another model that uses economic data releases and their "surprise" level in two different time zones (European trading session and US trading session) for intraday trading of EUR/USD and USD/JPY exchange rates is described in Tivegna 2003.

A well documented model that combines different inputs is the Citibank currency model (Ilmanen and Sayood 2002, p 47, Ilmanen and Byrne 2004, p 7). The models ranks six currencies by four inputs each month:
- *Carry,* measured by the deposit interest rate. According to the covered and uncovered interest rate parities, both the forward exchange rate and

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[34] Jobless claims, ISM (previously NAPM) manufacturing index, ISM (previously NAPM) non-manufacturing index, Philadelphia FED index, Chicago PMI index, retail sales (ex autos), retail sales, industrial production, non-farm payrolls, unemployment rate, average workweek length, personal consumption, personal income, index of leading indicators, conference board consumer sentiment index, preliminary Michigan consumer confidence, final Michigan consumer confidence, housing starts, new home sales, existing home sales, construction spending, domestic auto sales, factory orders, durable goods orders and real GDP (Hafeez 2002, p 98).

the expected future exchange rate of a currency with a higher deposit interest rate are lower than its spot rate. However, in reality the uncovered interest parity often does not hold; i.e., currencies with higher deposit interest rates do not depreciate as much as predicted by the covered interest rate parity (Rosenberg and Folkerts-Landau 2002, p 72).

- *Value indicator,* measured as the ratio of the forward exchange rate to its long-term average**.** When currency is overvalued relative to its long-term average then it is expected to depreciate and vice versa.
- *Policy tracking strategy,* measured as the monthly change in the 10-year government bond yield. Rising interest rates tend to support exchange rates as can be implied from the standard monetary model of exchange rate (for example, see Frankel and Rose 1995, p 1691–1692).
- *Currency momentum or trend indicator,* measured as the last 3 months' average return of the currency's exchange rate against USD.

Based on the average rank of the four predictors two monthly currency positions are initiated with forward contracts at the beginning of each month: buy the 1st currency against the 6th and the 2nd currency against the 5th. During the test period between January 1992 and September 2002, the model produced annualized Sharpe ratios of 0.86 and 0.41 for the two currency pairs. Corresponding hit ratios were 0.65 and 0.57 (Ilmanen and Sayood 2002, p 48).

In addition to the Citibank model, other authors have tried to combine different inputs to one exchange rate model. The model of First Quadrant (Darnell *et al.* 1997, p 9) combines purchasing power parity, a set of interest rate measures (short and long term) and a serial correlation factor capturing central bank intervention. The model produced on average 540 basis points of annual value added between April 1992 and December 1996 with an annualized Sharpe ratio of 0.81 (*ibid*, p 10). The model tested in ABN-AMRO bank combines trend, carry and changes in purchasing power parity into one model yielding an annual excess return of 3.7%, when applied to the nine most liquid currency pairs, with an information ratio 1.01 (Collins *et al.* 2005, p 81).

The Credit Agricole Indosuez currency model (Kotecha *et al.* 2003) trades EUR/USD, USD/JPY and GBP/USD currency pairs using five dynamically weighted inputs: a moving average crossover momentum indicator (optimized from thousands of combinations (*ibid,* p 2)), a positioning indicator based on IMM data from the Chicago Mercentile Exchange, an interest rate indicator, a option volume indicator and an economic activity surprise index. The results from each individual input are dynamically weighted according to their historical accuracy to produce an overall weekly signal. The performance statistics of the model are relatively good: cumulative annualized excess returns from the weekly strategy are from 18.9% to 30.4% (*ibid,* p 1), but over-

optimization of moving average crossover parameters[35], dynamic weighting of different inputs based on the last month's directional success ratio and a very short test period may imply that the actual performance of the model may significantly decline from the simulated one.

The JP Morgan's FX and Commodity barometer (Normand 2004) combines ten input signals that reflect changes in economic activity (economic surprise index and relative growth expectations), return levels (risk-adjusted spot and forward return levels in the interest rate and equity markets) and technical forces (trend indicator, risk level indicator, measures of investor's positions and portfolio flows). The signals are combined using Markowitz rolling weighting with a maximum of three signals allowed to have zero weights. The strategy produced an information ratio of 2.3 on a basket of 12 currencies (*ibid,* p 181).

From the model overviews given above it can be concluded that the risk-adjusted carry model based on short-term interest rates as the only input and FX market volatility as a risk factor would be a good candidate for estimating a single-factor model. For multi-factor models, the Citibank model would be a good starting point for empirical estimation because of its simplicity, lack of over-optimization, robustness, and good performance statistics.

1.5. Quantitative investment models for taking interest rate risk

1.5.1. The framework for analyzing possible inputs for quantitative fundamental investment models for taking interest rate risk

The range of possible inputs and methods for developing a model for positions in the IR market is as wide as it was in the case of the FX market. At the same time the range of different risk classes where excess return can be earned is much wider. The straightforward buy/sell positions (that are the only positions available in the FX market) in the IR market can be taken in various duration segments – from money markets up to 30–50 year bonds. It is even possible to target any specific part of the yield curve – for example, a 3-month interest rate 1.5 years from today. In addition to simple buy/sell positions the IR market offers the opportunity to also take different curve spreads (steepening- and flattening trades), curve shapes (butterfly and barbell trades) and cross-country yield spread positions and benefit from the structural time (term) premium.

The inputs that have been used in the models of directional buy/sell interest rate positions usually follow conventional theoretical frameworks. The LM equation in an IS-LM framework expresses the relationship between the real money supply, income level and real interest rates:

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[35] Lengths of moving averages used.

$$m - p = \alpha y - \beta r \qquad (13)$$

Rearranging and writing the real interest rate as a nominal interest rate minus inflation expectations, we get:

$$i = E(\pi) - \frac{1}{\beta}(m - p) + \frac{\alpha}{\beta} y \qquad (14)$$

where (all variables except the interest rate are in logarithms):
y – real income,
$E(\pi)$ – inflation expectations
m – money supply,
p – price level
i – nominal interest rate.

We can see from the equation that the higher the income levels and expectations of inflation are, the higher the interest rate levels should be, which translates into a "sell" signal for interest rate futures. A practical problem may arise in modeling as inflation expectations are not directly measurable. Possible solutions include the use of distributed lag of past inflation rates (see Feldstein and Eckstein 1970, p 365) or some published inflation forecasts.

In addition to the IS-LM framework the loanable funds equilibrium model (Caporale and Williams 1998, p 13) includes also the government's deficit (as an indicator of the supply of government bonds and bills) as a possible explanatory variable of interest rate levels. Although theoretically important and statistically significant in relatively older studies (for example, see Feldstein and Eckstein 1970, Blanchard 1984 and Hoelscher 1986), this factor has not had statistically significant predictive power in more contemporary studies (Vesilind 2003, p 11).

In investment decisions investors also focus on various value benchmarks between different asset classes (presuming that extreme deviations often serve as lead indicators of trend reversals) and investors often behave differently when they have different risk appetite levels. For example, in a paper by Normand (2002, p 4), the equity yield to bond yield ratio[36] as a value measure is used successfully to predict the price reversals in US 30-year bonds. Various risk appetite measures give an indication of the relative demand for government debt instruments compared to corporate debt and equities. When the overall risk appetite is high (low), then more (less) money is invested into riskier assets resulting in the decline (rise) of government bond prices (Normand 2002, p 5). The risk appetite level in bond markets can be calculated using the differences between government bond interest rate levels and interest rates of riskier

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[36] Calculated as an inverse of the P/E ratio of a wide national stock index to the long-term interest rate level and measuring the relative value of bond prices to equity prices.

instruments (for example, high yield debts, swap interest rate levels or emerging market debt interest rate levels).

In addition to the different indicators describing the general levels of interest rates, for yield curve spread trades there is also a need for indicators describing the relative movements in long-, medium- and short term interest rates within one country. One group of such variables is the different measures of carry (the difference between short- and long-term interest rates) that have been used to explain investors' willingness to invest their money into short-term vs. long-term interest rate products. Various differences in the values of input variables between different countries are useful to explain cross-country yield spread movements and to initiate corresponding trades.

Different technical inputs can also be and have been used in models for investment positions in IR markets. The use of technical indicators in interest rate markets has the same theoretical grounds as in forex and equity markets and is therefore not described here in more detail.

The models exploiting the term premium in yield curves are based on earning additional returns from the empirical finding[37] that the time expectations theory performs relatively poorly in describing the movements in the yield curve. This theory (or expectations hypothesis; for example, see Reilly and Brown 2003, pp 759–761) is based on the hypothesis that any long-term interest rate simply represents the geometric mean of current and future short-term interest rates expected to prevail. It means that following the theory the average shape of the yield curves over a long period should be flat. Instead, the yield curves have a mostly upward-sloping shape, which means that long-term interest rates contain besides forecasts of short-term interest rates also different premiums (see also Figure 4).

The reasons why yield curve shapes are mostly upward-sloping are explained by different theories; for example, the liquidity preference hypothesis and the segmented market hypothesis (also known as the preferred habitat theory). The theory of liquidity preference holds that long-term securities should provide higher returns than short-term obligations because investors are willing to sacrifice some yields to invest in short-maturity obligations to avoid the higher price volatility of long-maturity bonds (for example, see Reilly and Brown 2003, pp 761–762). The preferred habitat theory states that since investors prefer to hold short- rather than long-term bonds, the term premium will rise as the maturity of the bond increases (Mishkin 1992, p 817). The theory is further supported by the borrowers preferring to borrow money rather for a long- than for a short-term (Hull 2002, p 108). It has also been shown that if the markets are efficient, then the expected rate of return on any longer-term bond in excess of the spot rate is proportional to its standard deviation (Vasicek 1977).

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[37] For a list of some papers on this subject see Backus *et al.* 1998 p 1.
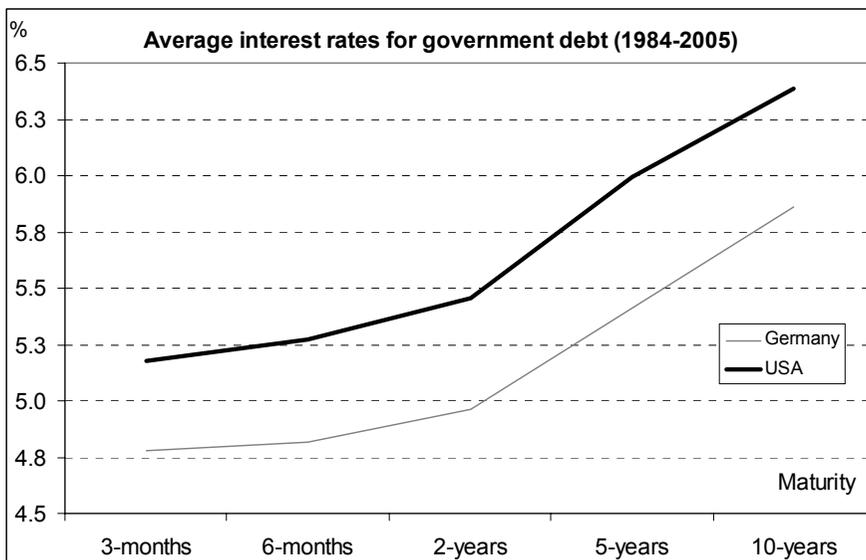
Figure 4. Average interest rates of the U.S. and Germany's government debt, data source: Bloomberg, authors' calculations.

The jump in the yield curve is usually the steepest around the 1-year maturity mark, because there are relatively larger amounts of money market funds (investing in maturities up to 1 year) operating in the world than debt funds with longer duration.[38] Therefore, the demand for debt instruments with maturities of 1 year or less is considerably higher than for debt instruments with higher maturities.

The term premium of longer-term bonds can be separately profited from using the futures of longer-term debt instruments. The price of a financial future is described by the following equation (Hull 2002, p 51):

$$F_0 = S_0 e^{(r-q)T} \tag{15}$$

where: F_0 is the price of the futures contract;
S_0 is the cash price of the cheapest-to-delivery bond;
T is the time until delivery (expiration of the futures contract);
r is the short-term interest rate and
q is the yield of the underlying security.

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[38] The fact that the yield curve deviations from expectations hypothesis are the largest for shorter maturities (less than 24 months) is studied for example in Backus *et al.* (1998 p 4).

We can see from the equation that in times when the yield curve is upward-sloping, then for the futures of longer-term debt securities before delivery $r<q$. This means that $(r-q)T<0$ and $F_0<S_0$. By the time of delivery T approaches zero and F_0 converges to S_0. When market conditions do not change, then (*ceteris paribus*) S_0 stays constant and F_0 converges (ie increases) to S_0. Therefore, we can conclude that as long as yield curves are mostly upward-sloping and the expectations hypothesis does not exactly hold, it should be possible to earn excess returns with a strategy of simply buying and holding futures of longer-term debt instruments.[39]

1.5.2. Previously used practical approaches and developed investment models for taking interest rate risk

The models built to earn excess return in interest rate markets can be divided into two categories: models that earn excess return from market timing decisions (different duration or spread positions) and models that earn excess return from exploiting structural inefficiencies. Below are some examples of the different interest rate models previously developed and their performance statistics if published:

- Multi-factor directional models
- Multi-factor yield curve spread models
- Multi-factor cross-country yield spread models
- models to profit from structural inefficiencies in IR markets

Examples of multi-factor directional models for longer-term government bonds are the models developed by A. Ilmanen (Ilmanen 1997 and Ilmanen and Sayood 2002) and the model developed by J Normand (Normand 2002). For U.S. Treasuries Ilmanen (1997) uses curve steepness, real yield, equity market strength and bond market momentum as inputs. For a model for German Bunds he adds the Commodity Research Bureau (CRB) commodity price index and the change in trade-weighted nominal exchange rate (Ilmanen and Sayood 2002, p 41) as timely proxies for inflation. These models were tested from January 1992 and the models gave monthly signals for self-financed long-short positions based on regression analysis and based on a rolling 10-years of past data. The

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[39] The above-described logic can lead further to somewhat surprising trading strategies. For example, buying and holding the futures of debt instruments against the futures of commodities. As for commodities the "yield of underlying security" or "q" is negative (as the commodities do not have interest payments, but do have storage costs) and therefore, for commodity futures $(r-q)T>0$ and $F_0>S_0$ before delivery (comment made by C. Satterfield from RQSI hedge fund during the discussion of the thesis). However, these strategies are left for future research.

annualized Sharpe ratio between January 1992 and September 2002 was 0.65 for the German Bund positions and 0.81 for the U.S. Treasury positions. The corresponding hit ratios were 0.57 and 0.62 (*ibid,* p 48).

The model by J. Normand (Normand 2002) combines fundamental factors (economic growth and inflation), value indicators (real yield and equity earnings yield to bond yield ratio), the risk appetite index (composition of high yield, swap and emerging market debt spreads) and technical indicators into a combined Bond Barometer. The model takes directional positions in the US 2-year, 5-year, 10-year and 30-year bonds with information ratios up to 1.30 (*ibid*, p 12).

The Citibank German yield curve spread model (Ilmanen and Sayood 2002, pp 41–43) serves as the best example of a multi-factor yield curve spread model. It trades duration-neutral German 2–10 year yield curve steepening/flattening trades based on a regression model on a rolling 10-years of past data. The following factors were used as inputs and added value also as single predictors: equity market momentum, business confidence momentum, inflation momentum and monetary policy momentum. The rolling yield (carry) and yield curve steepness as a mean reversion indicator were also used in regression, although they did not add value individually. The annualized Sharpe ratio for this strategy between January 1992 and September 2002 was 0.84 and the hit ratio was 0.60 (*ibid,* p 48).

The money market yield spread model described in Crawford (2003) trades the spread between the 2nd and 6th Eurodollar contracts (representing the expected 3-month interest rate levels correspondingly approximately 6 and 18 months from now). The model combines the fair value of the spread calculated using a modified Taylor rule with technical indicators and has a targeted information ratio of around 0.5.

The Citibank cross-country yield spread models (Ilmanen and Sayood 2002, pp 43–45) trade cross-country duration-neutral positions in seven-to ten-year bonds and two-year swaps. Each month two positions for both maturity sectors are taken out of six economic regions: Germany (a proxy for the EMU), the U.K., Sweden, the U.S., Canada and Japan. Each month the positions are based on the ranking of the regions based on the following inputs: yield curve steepness (carry), real yield, equity market strength and yield trend as a reversal indicator. The annualized Sharpe ratios between January 1992 and September 2002 were 1.26 and 0.69 for the two 7–10-year positions and 1.78 and 0.31 for the two 2-year positions. The hit ratios were 0.67 and 0.57 for the 7–10-year sector and 0.68 and 0.60 for the 2-year sector (*ibid,* p 48).

The State Street Global Advisors' model (SSGA 2003, pp 2–8) is designed to add value by exploiting the differential in returns between six developed bond markets (the USA, Europe, Japan, the UK, Canada and Australia). Their decision process combines model signals (with 7–10 year yield deflated by growth and inflation, yield curve steepness and the inverse of the stock wealth

as inputs) with fundamental forecasts from in-house economists. The performance statistics of the models are not disclosed.

For example, models designed to profit from the structural inefficiencies in the interest rate markets are reported by a leading global bond manager, PIMCO[40] (PIMCO 2005). Their model has produced simulated annualized excess return over the 3-month Libor during a 14-year period ending in September 2005: 9.7% in the 5th contract of U.S. 3-month futures, 8.51% in U.S. 5-year government bond futures, 8.05% in U.S. 10-year government bond futures, and 6.94% in U.S. 30-year government bond futures. However, it should be noted that this performance was achieved during a period of declining interest rates and the interest rate trend has not been eliminated from the results shown. Similar results have been reported by JP Morgan (Loeys and Fransolet 2004, p 8). They used U.S. 3-month forward interest rates during eight 3-month periods between maturities of 3 months and 21 months and found that the highest return to risk ratio can be achieved at the 3-month forward interest rate of the money market yield curve around a 12-month horizon, giving return to the risk ratio of 0.85.

The performance power of several single inputs is estimated in a paper by Ilmanen et al. (2002) where they find that during the last decade the best risk-adjusted returns were achieved by using the size of carry in country allocation strategies (*ibid*, p 4). For market timing trades a trade-weighted FX index as a proxy for inflation and a technical momentum indicator showed the best results and for yield curve spread positions different measures of future economic activity (equity market and business confidence momentum) and inflation were the most useful (*ibid*, p 5).

From the model overviews given above it can be concluded that a diversified set of investment models for IR markets should include separate models for duration positions, for yield curve positions, for cross-country yield spread positions, and for exploiting the structural time premium. The models developed by A. Ilmanen and other analysts in Citibank offer good starting points for estimating the models for duration, yield curve and cross-country yield spread positions. For models that would exploit the structural time premium it was decided to test all the different maturity sectors in order to find the sectors where the time premium can be the most efficiently profited from.

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[40] Pacific Investment Management Company

1.6.   Theoretical portfolio of active investment models

1.6.1.   Relative importance of different approaches and previous attempts to build a diversified investment portfolio

Speculative forces and investor sentiment are usually considered to be useful for predicting short-term movements in prices. Technical models are usually considered to be useful for taking medium-term active positions, while fundamental factors are consider to be more useful in the long-term. For example, a survey among FX dealers (Cheung *et al.* 2000, p 21) shows that 97% of FX dealers believe that fundamental factors have no role in determining intraday movements in the exchange rates, while 87% believed that long-term (over 6 months) movements in the exchange rates reflect changes in fundamental value. Technical factors were pointed out as the most important factor that explains exchange rate movements in 10.3% of the cases for intraday movements, in 26.3% of the cases for medium-term movements and in 11.3% of the cases for long-term movements. For intraday analysis the three most important factors pointed out were overreaction to news (32.8% of answers), bandwagon effects[41] (29.3% of answers) and speculative forces (25.3% of answers) (Cheung *et al.* 2000, p 21).

The attempts to build a diversified portfolio of different investment models can be divided into two philosophically different approaches. The first one tries to use some methodology to decide which weight to apply to each model at any given moment. The methodology can be based on a simple indicator or on a more complex setup such as portfolio theory.

McMahon (2004) serves as a good example of a simpler set-up. They used a "regime switching" indicator based on the relative implied volatilities in the options market to predict if the EUR/USD exchange rate will be in a "trending" or "ranging" environment. He showed that following the appropriate trading strategy predicted by the indicator (trend-following strategy during a "trending" regime and selling volatility during a "ranging" regime) gives better results than using a strategy where both investment styles get a fixed 50% of the notional capital. Corresponding information ratios were 1.14 and 0.96 (*ibid,* p 5). Later, the author (McMahon and Anderson, 2005) also added speculative positioning data and regime persistence measure as inputs to the "regime switching" indicator and used variable scaling based on the relative probability of predicted "regimes" instead of fixed 100%/100% scaling. The results obtained were similar to the previous ones. More advanced studies can use some modification of portfolio theory or use the results from simulating different market conditions (for example, see SSGA 2003, pp 3–4) in order to get weights that would perform as well in diverse market situations as possible.

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[41] Investors, seeing an emerging trend, often quickly enter the market in the same direction in attempt to profit from the trend (www.investopedia.com).

The second attempts try to combine several inputs, markets and models with fixed weights during all time periods with the hope that a poorer performance of any given model in any given market is compensated for by a better performance of another model in another market. The most successful attempts in that direction have been made by A. Ilmanen and his colleges (Ilmanen and Sayood 2002, Ilmanen *et al.* 2002). They showed that combining five models (a model for duration positions, a model for yield curve positions, models for cross-country yield spread positions in 2-year and 10-year maturity sectors and a model for currency positions) the hit ratio of any single model around 0.57 can be increased to 0.7 and the annualized Sharpe ratios of individual models between 0.7–1.0 can be increased to 1.5. However, their portfolios did not include models based solely on past price data and models based solely on exploiting structural risk premiums in foreign exchange and interest rates. Their models were tested with cash instruments (instead of derivatives) that led to relatively high transaction costs in practical implementation. Their portfolio also did not use optimization or any regime switching indicators in determining the weights of each model – fixed weights giving equal monthly volatility to each model were used during all test periods.

1.6.2. Theoretical framework for empirical estimation

The strong theoretical background, extent of diversification, availability of input variables and good historical performance results of the models described in Ilmanen and Sayood (2002) were the reasons why in this thesis it was decided to base all multi-factor fundamental models (currency model, yield curve model, cross-country yield curve model and duration model) on the ideas and framework of these models. This thesis goes further from the diversification attempts made by A. Ilmanen *et al.* and adds the following new knowledge:

- The thesis widens the number of markets under consideration – from six regions used in Ilmanen's research to ten;
- The thesis tests the models on more recent data and replaces some input variables with ones that have better predictive power;
- Instead of cash instruments all of the models are tested using derivative instruments, which reduces the transaction costs and gives the possibility to implement (and measure the return and risk of) active return strategies completely separately from the investment decisions of the benchmark portfolio;
- The thesis adds models based solely on price data (models using technical analysis and models using univariate autoregressive techniques) and models based on structural risk premiums to the overall portfolio of models;
- The thesis tests if more advanced weighting schemes to combine different models into one diversified investment portfolio (weighting

based on traditional portfolio theory and based on leptokurtic portfolio theory) give statistically significant improvement of excess returns compared to naïve weighting schemes with fixed weights.

The final set of models/approaches chosen for estimation were the following (see Table 2):

Table 2. The final set of models chosen for estimation

Risk class / Investment style (model)	Models using only price data	Models using only one main fundamental input	Models using more than one fundamental input
Currency risk	Moving average crossover and ARMA models	Currency model based on risk-adjusted carry	10-currency model with four ranked inputs
Duration risk		Long-only structural model	Econometric duration model with multiple inputs
Yield curve risk			Econometric yield curve model with multiple inputs
Cross-country yield curve risk			Cross-country yield spread model with four ranked inputs

The above-described set of different approaches covers mostly the matrix of available risk classes and different investment styles/models used profitably in currency and debt markets. The approach can be further diversified by adding credit and volatility risks as risk classes and very short-term intraday technical models as an investment style. These possible additions are left for future research.

The subject of how to measure and limit the risk of active investment positions is also left mainly outside of the scope of this thesis. As the risk tolerance of different investors is very different, then suitable solutions also vary. One can use separate direct risk limits for each risk class or a more universal VaR framework that is used in Eesti Pank, for example (Vesilind and Kuus 2005, p 14).

To construct a diversified investment portfolio it was decided to compare both portfolio construction methodologies described in chapter 1.1.3. In addition, a simpler portfolio that gives equal volatility to each model with the same amount of traded variables (i.e., volatility x to a model trading 1

instrument, volatility 2x to a model trading 2 instruments and volatility *n*x to a model trading *n* instruments) was calculated for comparison to test if the use of more advanced techniques (as opposed to naïve fixed weights) to get optimal and variable weights for the positions in each model will increase the returns of the entire investment portfolio in a statistically significant amount.

The volatility and return statistics and the correlations between individual models used for calculating the optimal weights were calculated using the data of the entire test period. The given approach cannot avoid possible criticism: having the data for the entire test period as an input for calculating the weights of different positions can create a forward-looking bias, as this data was not available at the beginning of the test period. At the same time, the simulation period (14 years) is relatively short for only using variable weights based strictly on the data before the test period. As for calculating meaningful and stable return, risk and correlation statistics one needs data from at least one full business cycle (7–8 years). This aspect (i.e., a possible forward-looking bias) will be considered when the superiority of one portfolio over another is tested using a methodology proposed by White (2000).

2. EMPIRICAL ESTIMATION OF A PORTFOLIO OF QUANTITATIVE ACTIVE INVESTMENT MODELS

2.1. Estimation period and methodology

All the models are tested during a 14-year (168-month) period starting on December 31, 1992 and ending on December 31, 2006. The length of the test period was mostly constrained by the availability of data and the convergence of business cycles and financial markets data in the Eurozone in the early 1990s.[42] The data sources were Reuters EcoWin, Bloomberg and *Consensus Forecasts*.

All the models are implemented using derivative instruments (forward or swap contracts or futures), the main reason being the relatively lower share of trading costs in the returns achievable with using leverage. As the "rational efficient market formulation" theory by Grossman and Stiglitz (1980) states that there are only a certain "equilibrium amount of inefficiencies" in the markets, then using the instruments that enable the investor to take high leverage compared to the trading and portfolio management costs increases the chances of earning positive excess returns after the additional costs of active management are deducted.

The use of derivatives means that the results of the estimated models reflect pure excess return that can be earned over a pre-determined benchmark: the funds invested according to the pre-determined benchmark can act just as collateral for the derivative portfolio as long as they are invested in liquid financial instruments (bonds, deposits, money-market instruments, etc). In this way, the returns from the benchmark portfolio can be clearly separated from the returns achieved from the decisions to deviate from the pre-given benchmark and the excess returns from active decisions can be compared to a "zero" benchmark. The use of derivative instruments also enables the investor to minimize foreign exchange risk while taking interest rate views: as the positions

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[42] A three-stage process of European integration that ended with the introduction of the single currency (euro) started on July 1, 1990, with the aim to achieve the free movement of capital between member states, a closer co-ordination of economic policies and closer co-operation between central banks (Bloomberg Financial Definition). Therefore, we can assume a major breakpoint in European financial data and its relations with other variables (domestic non-financial economic data, financial data of the rest of the world) in the early 1990s.

are opened and closed to the same value (maturity) date, then foreign exchange movements have effect only on the profits and losses of the positions, but not on the underlying nominal amount.

However, the use of derivative instruments means that the models developed in the thesis are suitable only for relatively large investors. For example, the nominal size of a 10-year government bond futures' contract in Japan is 100 million JPY (source: Bloomberg). This means that with buying or selling only the absolutely minimum amount possible, namely one contract, an investor has to be prepared for a loss in the amount of 1 million JPY (about 6 500 euro) if the price moves only 1% in the opposite direction. With forward contracts in currency markets the trading costs deducted in this thesis are for an investor having individual positions with sizes of 1 million euros or larger.

The use of derivative instruments enables investors to scale the risk exactly according to their risk tolerance level. Investors who do not want to have leveraged positions may hold a 100% collateral, whereas investors who want to have the maximum amount of leverage may use only the minimum margin requirements of the futures exchanges or trading partners. Therefore, the reader (investor) should pay more attention to the different risk-return ratios presented for the simulations than to the return and risk statistics alone, as these can be leveraged up to earn a higher return.

The results from the currency positions tested are calculated as a percentage of the underlying capital (nominal position size), as this is the measurement convention used in financial literature. However, the results from interest rate positions are calculated in euro and in absolute terms. There are two reasons for doing that. First, as the interest rate futures are derivative instruments and enable high levels of leverage, then percentage returns depend on the amount of leverage – we can get huge returns when only minimum margin requirements are used (for example, the minimum margin requirement for one contract of a US 3-month interest rate future is only 743 USD, while the contract size is 1 million USD, and the value of 1 full point of movement in the price is 2,500 USD)[43] and relatively small returns when the nominal contract size or contract values are used.[44] Measuring the returns in euro gives at the same time a clear and straightforward picture of the returns available from a certain number of contracts, giving the investor the possibility of choosing his or her own target leverage level. To help the reader in that, the nominal sizes of the futures'

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[43] Source: Bloomberg
[44] For example, the tests of some of the models presented in this thesis showed that depending on the level of leverage the excess returns in percentages of the entire portfolio can vary between 0.97% and 122.4%, with monthly standard deviations of the excess returns between 0.17% and 21.0% (Vesilind 2006 p 27) if we also consider the maximum drawdown the models had during the simulation period. The return and volatility levels in percentages can be even up to four times higher if we calculate the returns based only on the minimum margin requirements of corresponding exchanges.

contracts with minimum margin requirements are also given in subchapter 2.2.2.

The second reason for calculating the return in euro is the fact that the futures contracts have relatively large nominal contract sizes and the contracts are not divisible.[45] Therefore, it is more convenient to invest in a certain and fixed number of futures contracts than into a variable number of futures contracts in order to retain a fixed total value, which would be required for calculating a mathematically correct percentage return.

As the excess returns from interest rate positions are calculated in absolute terms (in euro), then the excess returns of the combined portfolio are also calculated in absolute terms (in euro). The sizes of the positions provided in the thesis are hypothetical and can be changed according to the investors' preferences.

The descriptive statistics calculated for each model and later for the entire portfolio are divided into three groups: different statistics measuring the excess return, different statistics measuring risk and volatility, and different statistics that combine the return and risk and show the lengths of the drawback periods. The statistics calculated are:

- Return statistics:
    - Cumulative excess return over the test period.
    - Average annual excess return.
    - Average monthly excess return
- Risk and volatility statistics:
    - Standard deviation of the average monthly excess return.
    - Maximum monthly excess return.
    - Minimum monthly excess return.
    - Maximum drawdown.
- Different return and risk ratios and the lengths of drawback periods:

    - Annualized Sharpe ratio. Calculated as $\sqrt{n}\,\dfrac{r_{excess}}{stdev(r_{excess})}$, where n is the number of observation periods in a year (in case of monthly positions $n=12$), r_{excess} is the average monthly excess return and *stdev (r_{excess})* is the standard deviation of the average monthly excess return. The original Sharpe ratio (see Sharpe 1994) uses the difference between the return of the active portfolio and the return of the benchmark portfolio both in the numerator and for the calculation of the standard deviation. As in our model all the positions are taken using derivative instruments, the return of the benchmark portfolio is

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[45] For example, the future of a Japanese 10-year government bond has a nominal and indivisible size of 100 million yen (source: Bloomberg).

constantly zero and in this way cancels out from the calcu-
lations.
- o Accuracy (the number of months with positive performance divided by the total number of months with nonzero performance).
- o Profit factor (gross profit divided by gross loss).
- o Longest flat period (the length of the period without a new equity high) in days (for models where signals are re-calculated daily) or months (for models where signals are re-calculated monthly).

The above-described set of descriptive statistics provides a good overview of both the return and risk side of the estimated models. The most important among them is the Sharpe ratio (sometimes referred to as the "Information ratio"), which is most often presented in different papers that compare the results of investment models or money managers. The median annualized Sharpe ratio for active managers is usually 0.5 or lower. For example, the 10-year median information ratio from April 1995 to March 2005 for active currency managers was 0.5, for active global emerging market debt and for active global equity managers 0.4, and for active global fixed income hedge funds 0.2 (Collins et al. 2005, p 76). The information ratio of the excess returns achieved with investing in the S&P 500 equity index instead of the US 1-month deposit interest rate was 0.27 (author's calculations, data from 1934 to 2006).

In addition to the statistics presented above the statistical properties of the distributions of the excess returns are shown in Appendix 7. These statistics can be used to answer the question if the excess returns are normally distributed, and to get an overview on the kurtosis and skeweness of the distributions.

2.2. Analysis of market data, liquidity and trading costs

2.2.1. Foreign exchange market data, liquidity and trading costs

Foreign exchange markets are very liquid and trading is possible 24 hours a day. The daily trading volume was $1.9 trillion in 2004 (BIS 2005, p 9), approximately 20 times larger than the daily trading volume of the New York Stock Exchange and the Nasdaq combined (Lien 2006, p 1). The market is the most liquid and also the most volatile during the European session (9.00–19.00 Estonian time), followed by the U.S (15.00–24.00 Estonian time) and Asian (02.00–11.00 Estonian time) sessions. The liquidity between 24.00 and 02.00 is relatively low and this period is also covered from New York (*ibid,* p 63–69).

The daily close prices are fixed in Bloomberg either at 24.00 Estonian time (New York close), 20.00 Estonian time (London close) or 13.00 Estonian time (Tokyo close). For a 24-hour market the daily close prices are also open prices

for the next day. This fact has to be remembered in interpreting the results of the simulations as the usual back-testing rules use close prices to calculate the signals, while the trades are initiated at the next open. As in the FX markets the close and the following open are the same (except after weekends and holidays), then a small slippage due to the time needed to calculate model signals and implement the trades is unavoidable. In this thesis it is assumed to be zero, as there is no reason to expect the average small slippage to be materially positive or negative over a longer time period, considering that the slippage happens during a very short time frame during the night trading session, which has a lower volatility compared to the daytime sessions.

The trading costs for institutional clients in the foreign exchange markets consist mainly of bid-ask spreads. The average bid-ask spreads of different cross-currency pairs are presented in Table 3 (for the description of the source see footnote 46):

Table 3. Average bid-ask spreads of different cross-currency pairs (%)

	USD	EUR	JPY	CAD	GBP	SEK	NOK	AUD	NZD	CHF
USD	X	0.008	0.018	0.025	0.011	0.026	0.031	0.039	0.042	0.024
EUR	0.008	X	0.022	0.034	0.030	0.027	0.032	0.050	0.052	0.013
JPY	0.018	0.022	X	0.043	0.025	0.055	0.061	0.059	0.064	0.023
CAD	0.025	0.034	0.043	X	0.037	0.051	0.056	0.077	0.060	0.038
GBP	0.011	0.030	0.025	0.037	X	0.036	0.043	0.063	0.058	0.022
SEK	0.026	0.027	0.055	0.051	0.036	X	0.067	0.092	0.069	0.041
NOK	0.031	0.032	0.061	0.056	0.043	0.067	X	0.096	0.076	0.049
AUD	0.039	0.050	0.059	0.077	0.063	0.092	0.096	X	0.100	0.062
NZD	0.042	0.052	0.064	0.060	0.058	0.069	0.076	0.100	X	0.068
CHF	0.024	0.013	0.023	0.038	0.022	0.041	0.049	0.062	0.068	X

When an active currency view is implemented using forward contracts, then the interest rate difference in the two countries has to be considered to calculate the forward exchange rates. These interest rates also have bid-ask spreads, which are approximately 1–4 bp (0.01% – 0.04%) depending on the currency pair.[46]

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[46] The data is based on the differences between bid-ask quotes during the European trading session in institutional forex trading platforms Click and Trade (Dresdner Bank), CitiFX Trader (Citigroup) and UBS FX Trader (UBS Bank), April 2006. Authors' observations and calculations.

2.2.2. Interest rate market data, liquidity and trading costs

For implementing active views in interest rate markets the futures of debt instruments have the lowest trading costs and the highest liquidity. For the government bond markets considered in the thesis the following futures are available and tradable with the following trading times, open and close fixing times and bid-ask spreads (see Table 4):

Table 4. Available government bond futures, their trading times, open and close fixing times and average bid-ask spreads[47]

Country	Maturity	Trading times (GMT+2 h)	Open fixing	Close fixing	Average bid-ask spread
USA	30 years	03.00–00.00	15.20	22.00	0.5/32*
	10 years	03.00–00.00	15.20	22.00	0.5/32
	5 years	03.00–00.00	15.20	22.00	0.5/32
	2 years	03.00–00.00	15.20	22.00	0.5/32
Canada	10 years	15.20–22.00	15.20	22.00	0.02
	2 years	15.20–22.00	15.20	22.00	Not liquid
UK	10 years	10.00–20.00	10.00	20.00	0.01
Germany	10 years	09.00–23.00	09.00	23.00	0.01
	5 years	09.00–23.00	09.00	23.00	0.01
	2 years	09.00–23.00	09.00	23.00	0.01
Japan	10 years	03.00–05.00; 06.30–9.00; 9.30–12.00	03.00	09.00	0.02
	10 years (LIFFE)**	10.00–19.00	10.00	19.00	0.02
	5 years	Almost no trading			
Australia	10 years	01.32–09.30; 10.12–00.00	01.32	09.30	0.005 in price, ab 0.04 in value***
	3 years	01.30–09.30; 10.10–00.00;	01.30	09.30	0.005 in price, ab 0.03 in value

* Prices of the U.S. futures are quoted not in the decimal system, but in 1/32ths.
** The Japanese 10-year government bond future trading in LIFFE is rolled on to Tokyo with the next Tokyo open.
*** See the specifics of calculating the value of Australian government bond futures from price in Appendix 5.

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[47] Bloomberg data is used for trading and fixing times and data from corresponding futures exchanges is used for bid-ask spreads. Open interest and total volume functions in Bloomberg is used for monitoring liquidity. June 2006.

We can see from the table that liquid 10-year futures are available in all six countries, 5-year futures in the USA and Germany and 2–3 year futures in the USA, Germany and Australia. The only trading time when investors can trade all the abovementioned futures simultaneously is between 15.20–19.00. At all other times at least one of the markets is closed.

The daily close prices are fixed at different times (from 01.30 in Australia to 23.00 in Germany). Therefore, possible errors (slippages) that can arise from using data that is taken at different times of the day have to also be considered.[48]

For shorter maturities the following futures are available (see Table 5):

Table 5. Available interest rate futures, their trading times, open and close fixing times and average bid-ask spreads (source: see footnote 47).

Country	Maturity	Trading times	Open fixing	Close fixing	Average bid-ask spread
USA	30 day	03.01–22.00	15.20	22.00	0.005
	90 day	01.00–22.00	15.20	22.00	0.005
Canada	90 day	15.20–22.00	15.20	22.00	0.005*
UK	90 day	09.30–20.00	09.30	20.00	0.01
Eurozone	30 day	09.00–20.00	09.00	20.00	Not liquid
	90 day	09.00–20.00	09.00	20.00	0.005
Japan	90 day	15.20–22.00	15.20	22.00	Not liquid
Switzerland	90 day	09.30–20.00	09.30	20.00	0.01*
Australia	30 day	10.14–00.00; 01.34–09.30	01.34	09.30	Not liquid
	90 day	10.08–00.00; 01.28–09.30	01.28	09.30	0.01 in price, ab 0.02 in value

* Liquid markets for first contracts, liquidity declines sharply from the 4th–5th contract.

Futures contracts have a certain settlement date, which is usually in December, March, June or September of each year.[49] To back-test trading strategies based on futures, a continuous price series has to be formed from subsequent actual historical futures. The continuous (generic) future can be calculated from actual historical futures using either a difference adjusted methodology or ratio adjusted methodology. The first one preserves the movements of prices in abso-

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[48] The author did not have access to intraday data that would have enabled the fixing of the prices in different markets at the same time each day.

[49] For some futures also contracts with settlement days in other months exist, but they have much lower liquidity.

lute terms, the other one preserves the movements of prices in relative terms. Depending on the purpose of the back-test (i.e., whether absolute or relative return has to be calculated), one has to correspondingly use the difference adjusted or ratio adjusted generic future.

To get an overview of the minimum trading capital needed, Table 6 shows the nominal contract sizes of the futures used in the thesis together with the initial and maintenance margin requirements. As it can be seen from the table, the initial and maintenance margins are relatively small considering the nominal sizes of the contracts, meaning that in order to avoid margin calls considerably more capital is needed for successful trading than the minimum margin requirements presented. Source: Bloomberg.

Table 6. Nominal contract sizes and margin requirements of the futures' contracts used in the thesis

Contract	Nominal size	Initial margin	Maintenance margin
US 10-year future	100 000 USD	1013 USD	750 USD
Canadian 10-year future	100 000 CAD	1400 CAD	1300 CAD
Australian 10-year future	100 000 AUD	2800 AUD	2800 AUD
German 10-year future	100 000 EUR	1400 EUR	1400 EUR
Japanese 10-year future	100 000 000 JPY	880 000 JPY	880 000 JPY
UK 10-year future	100 000 GBP	960 GBP	960 GBP
US 5-year future	100 000 USD	743 USD	550 USD
German 5-year future	100 000 EUR	800 EUR	800 EUR
Australian 3-year future	100 000 AUD	950 AUD	950 AUD
US 2-year future	200 000 USD	675 USD	500 USD
German 2-year future	100 000 EUR	350 EUR	350 EUR
US 3-month future	1 000 000 USD	743 USD	550 USD
Canadian 3-month future	1 000 000 CAD	350 CAD	350 CAD
Australian 3-month future	1 000 000 AUD	750 AUD	750 AUD
German 3-month future	1 000 000 EUR	475 EUR	475 EUR
UK 3-month future	500 000 GBP	225 GBP	225 GBP

In countries where futures are not available, forward contracts on bonds have to be used. The average spreads based on Bloomberg data (function ALLQ, that shows the real-time bid and ask quotes from all major market participants) and the author's own trading experience in the Bank of Estonia are the following (data as of April 2006):

Swedish government bonds: 0.125 points in price[50]
Norwegian government bonds: 0.225 points in price
New-Zeland government bonds: 0.18 points in price
The liquidity of the government bonds of Switzerland was so low that it was decided to exclude them from further analysis.

For historical back-testing a generic time series has to be formed from actual bonds as was done with futures. The most convenient way to do that is to use Citibank world government bond indexes for the 7–10 year maturity sector. To use the indexes for overlay style testing, the short-term interest rate has to be deducted from the return of the bond index. As the indexes use the actual close prices of the bonds in given countries, then it is not possible to get the prices for different countries at the same time within each day, as was the case with futures. The slippage and possible errors in back-tests that can arise from this fact have to be taken into account while interpreting the results.

2.2.3. Other costs and fees

The trading costs in the thesis are deducted for the positions of each model separately. However, in practice it may happen that multiple models have opposite positions in the same market at the same time. Therefore, the trading costs in the thesis are more likely to be overestimated than underestimated, as in such situations the "netting" of the different investment positions from different models results in smaller trading costs than assumed in the thesis.

Besides direct trading costs management and performance fees have also been deducted from the simulated results in different studies. For example, Gencay *et al.* (Gencay *et al.* 2003, p 913) deduct a 2% monthly management fee and a 20% performance fee on net profits to more realistically simulate the actual fund environment. This can be justified, if one wants to compare the results of the simulated models to actual fund managers who report the performance they have offered to investors net of all management and performance fees.

In this thesis management and performance fees are not deducted, as no comparison with actual fund managers is made. The author also believes that it is reasonable to assume no additional costs for software, trading platforms and risk management, as a typical institutional investor already has (from his or her passive management business) suitable software, trading platforms and risk management systems to implement the trades and monitor the risk associated with the trades described in the thesis.

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[50] For a bond with a nominal value of 100 local currency units and trading at, below or above 100 local currency units depending on the bonds' time to maturity, its coupon rate and prevailing interest rate levels.

However, the author admits that implementing the models developed in the thesis in practice needs extra time and attention compared to passive management. The deduction of appropriate sums for compensation for the extra time needed to calculate model signals, trade the positions and monitor the performance (the amount of time estimated by the author to be around one full-time job) depends on the conditions in the investor's local job market and does not depend very much on the sizes of the positions traded. Therefore, the larger the sizes of the positions traded are, the smaller the share (up to the point when they can be neglected) of the costs of the time needed for trading the models in the cumulative excess returns are.

2.3. Estimation of investment models based only on the price data of the traded instrument

2.3.1. Purely technical models based on two moving averages

The first goal in developing a purely technical model was to keep the model as simple as possible in order to avoid over-fitting. There is always a possibility to develop more complex technical trading strategies, but as was mentioned already in chapter 1.1.2, it is easier to improve the performance of the entire investment portfolio by including more different investment strategies, than with trying to improve any single existing strategy.

The strategy that uses the crossover points of two moving averages with different lengths is one of the simplest strategies used in technical analysis (Schwager 1996, pp 53–56 and 602–603). The strategy creates a buy signal when the shorter moving average moves above the longer moving average and a sell signal is created when the shorter moving average moves below the longer moving average. The strategy in its purest form is almost never neutral, except during the times when the values of the short and long moving averages are equal. The moving averages are usually calculated using the close prices of any certain period of time (hour, day, week, month, etc.) and the trade is initiated with the open price of the next period. The trade is kept open until the two moving averages cross over again and give an opposite signal.

The lengths of the moving averages for the daily model described in the thesis were chosen arbitrarily as 5 and 50 business days. The lengths of the moving averages were not optimized, because as we can see from Figure 5, the optimal lengths are different during different time periods. This means that a strategy optimized on historical data is not necessarily consistently more profitable than a strategy based on arbitrarily chosen fixed lengths of time for the two moving averages.

In the figure, the annualized Sharpe ratios of the excess returns achievable from different moving average crossover strategies for USD/JPY exchange rates are simulated for different time periods. Three 10-year time periods are considered: from 1976 to 1985, from 1986 to 1995, and from 1996 to 2005. The model is daily. At the end of each trading day the trading signal is calculated based on the two moving averages whose lengths are shown on two horizontal axes. The trade is initiated with a 1-day forward contract with the next open price (if the moving averages gave an opposite trading signal than the day before) or rolled over for the next day with a 1-day swap if the trading signal stayed the same. Trading costs are deducted. The horizontal axes show the annualized Sharpe ratios achieved from each moving average pair tested.

We can see from the figure that during the period 1976–1985 the best result was achieved by using 1–10 day short moving averages together with 10–40 day or 100–140 day long moving averages (Annualized Sharpe ratios in excess of 1). During the period 1986–1995 the best performance was achieved by 70–80 day long moving averages (Annualized Sharpe ratios between 0.8 and 1.2 for different short moving averages) and during the last decade investors should have used the 40 day short moving average together with 100–120 day long moving averages (Annualized Sharpe ratios over 0.5).

The moving average crossover strategy based on 5- and 50-day moving averages was tested on the two most liquid currency positions (USD exchange rates against JPY and EUR) and on the two most liquid interest rate positions (10-year interest rate futures in the USA and Germany). A long position was held during the days, when the 5-day moving average exceeded the 50-day moving average at the previous day's close and a short position was held in the opposite case. The currency positions were initiated with 1-day forward contracts and if the position stayed the same during the next day too, then swapped forward with a 1-day swap. The interest rate positions were initiated with 10-year government bond futures (1 contract in each country).

The curves of the cumulative excess returns from currency positions are shown in Figure 6 and the performance statistics in Table 7. The excess returns are calculated as a percentage of the fixed notional capital[51] in forward contracts and swaps. The profits/losses from USD/JPY positions were calculated to euro at the end of each trading day.

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[51] The size of the notional capital depends on the targeted leverage level of the investor and is irrelevant in calculating the returns in percents.
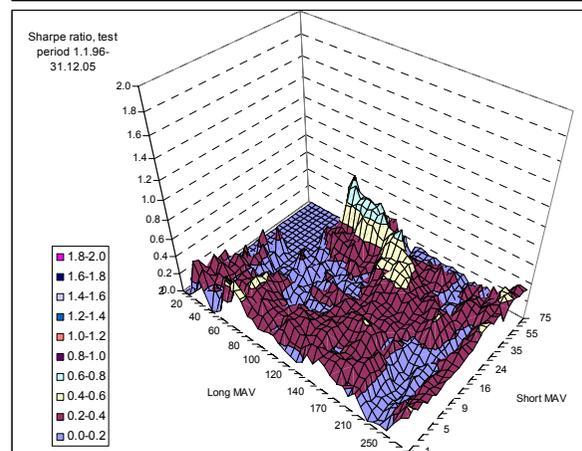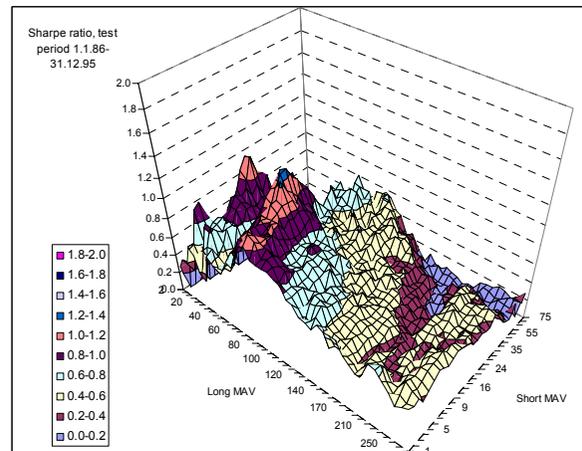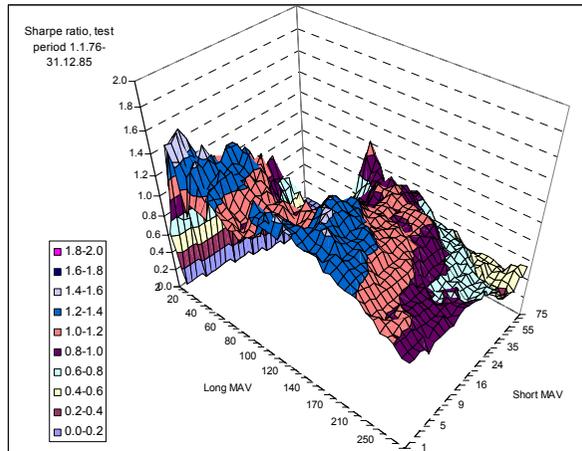
Figure 5. Annualized Sharpe ratios of strategies with different moving average lengths for USD/JPY exchange rates during three sub-periods: 1976–1985, 1986–1995, and 1996–2005.
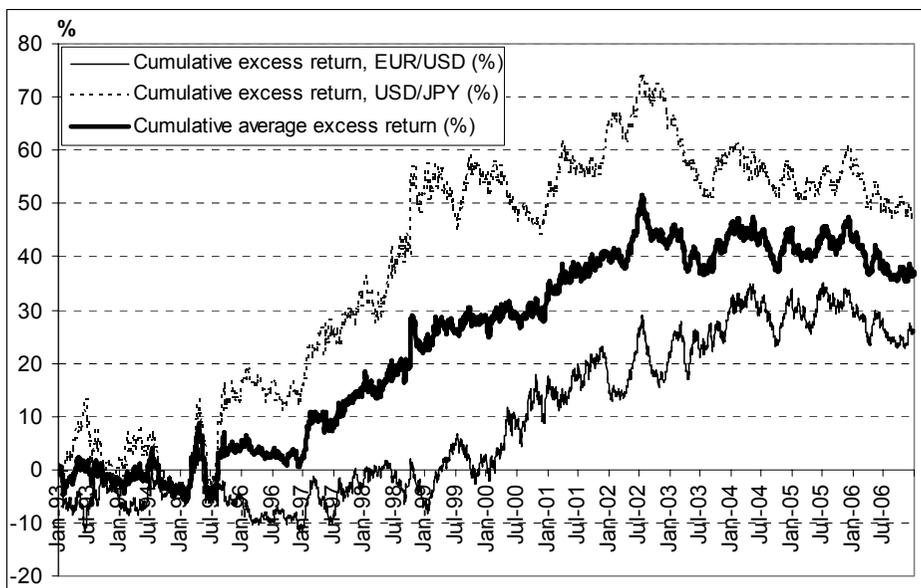
Figure 6. Simulated cumulative excess returns from USD/EUR and USD/JPY currency pairs using 5- and 50-day moving averages.

Table 7. Simulated results and selected statistics of the currency positions.

Statistics	Average	USD/EUR	USD/JPY
Cumulative excess return (%)	37.16	26.30	48.01
Average monthly excess return (%)	0.22	0.16	0.29
Standard deviation of average monthly excess return (%)	2.21	2.62	3.16
Sharpe ratio, annualized	0.33	0.19	0.31
Maximum monthly excess return (%)	8.10	6.26	15.44
Minimum monthly excess return (%)	−9.21	−8.28	−10.14
Accuracy	0.52	0.51	0.51
Profit factor	1.06	1.03	1.05
Maximum drawdown (%)	−16.14	−15.65	−27.27
Longest flat period (days)	1 163	1 075	1 163
Average yearly excess return (%)	2.65	1.88	3.43

We can see from the figure and table that a simple strategy based on two different moving averages has produced positive investment results during the

test period. The excess returns were the largest between 1997 and 2001, and more modest before and after that time period. On average, 51% of the days tested yielded a positive excess return and 49% of days yielded a negative excess return.

Although the performance statistics of the excess returns are similar to the ones achieved in previous tests (see chapter 1.3.2), they are not very impressive. The annualized Sharpe ratio of the currency portfolio was only 0.33 and the length of the longest flat period was longer than four years. The average monthly return of one position was 0.22%, which corresponds to 2 200 euro if the forward contracts and swaps would have been initiated with a notional amount of 1 million euros. The reduction in profitability during the last years is similar to the reports on the decline in prediction power of simpler (technical) models presented in Olson (2004), Loeys and Fransolet (2004) and Normand *et al.* (2004).

The curves of the cumulative excess returns from the interest rate positions are shown in Figure 7 and the performance statistics in Table 8. The curves show the excess return from 1 contract of US 10-year government bond futures with a contract value of 100 000 USD and minimum initial margin of 1013 USD, and from 1 contract of German 10-year government bond futures with a contract value of 100 000 euros and an initial minimum margin of 1400 euros. The curve of the average excess return is an arithmetic average of the excess returns from both countries.
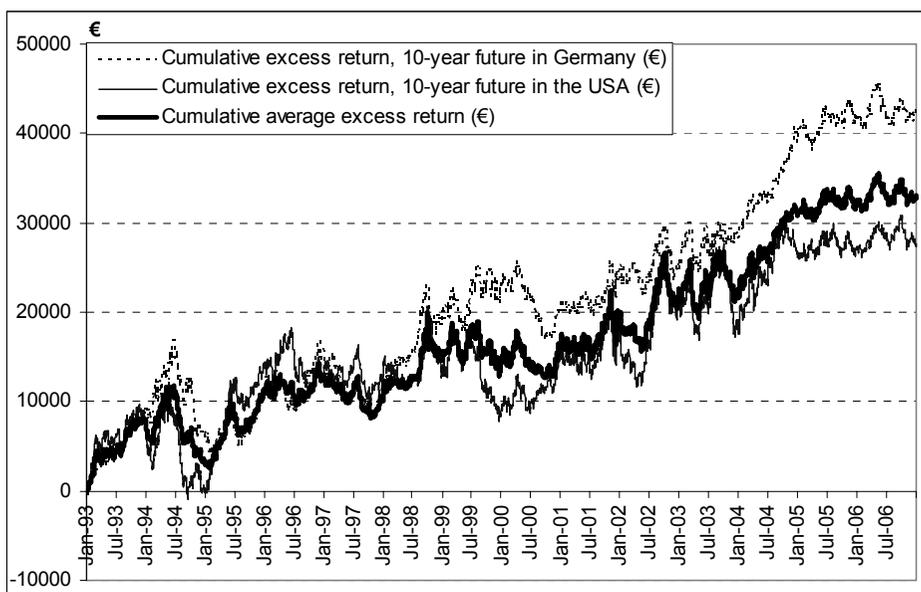
Figure 7. Simulated cumulative excess returns from 10-year interest rate futures in the USA and Germany using 5- and 50-day moving averages.

Table 8. Simulated results and selected statistics of the interest rate positions.

Statistics	Average	Germany	USA
Cumulative excess return (€)	33 039	42 730	27 734
Average monthly excess return (€)	197	254	165
Standard deviation of average monthly excess return (€)	1 494	1 666	1 963
Sharpe ratio, annualized	0.50	0.55	0.31
Maximum monthly excess return (€)	3 879	4 250	6 781
Minimum monthly excess return (€)	–4 783	–4 830	–5 953
Accuracy	0.53	0.53	0.52
Profit factor	1.09	1.10	1.05
Maximum drawdown (€)	–9 249	–12 890	–12 922
Longest flat period (days)	797	1078	801
Average yearly excess return (€)	2 360	3 052	1 981

We can see from the figure and table that a simple strategy based on two different moving averages worked in the interest rate markets slightly better than in the currency markets. We can also see that unlike the tests in the currency markets, the strategy did not lose its predicting power during the last 3–4 years in the interest rate markets.

The annualized Sharpe ratio of the interest rate portfolio was 0.5 and the length of the longest flat period was longer than three years. The maximum cumulative drawdown of 9 249 euros (as an average of the two positions) means that the minimum amount of capital the investor would have needed to trade the strategy successfully would have been about 7–9 times larger than the minimum initial margin requirement. The average monthly excess return in percentage terms was about 0.2% of the notional capital (the value of futures' contracts).

The analysis of the statistical properties of the daily excess returns from the two models (presented in Appendix 7) reveals that neither the excess returns from the currency model nor the excess returns from the interest rate model are normally distributed. The kurtosis of over 5 of the distributions of the excess returns from both models shows that the excess returns have a leptokurtic distribution and negative skewness of both excess return series shows that the series have longer left tails than the normal distribution.

2.3.2. ARMA models with seasonal factors

ARMA models were estimated on the same daily data as the moving average models: on the USD exchange rate against EUR and JPY and on U.S. and German interest rate markets. Before estimation stationarity tests were carried out for the entire sample period (January 1st 1992[52] – December 31st 2006, see Appendix 1 for test results). The results indicated that both the futures' series and the logarithms of the exchange rate series were stationary in the first differences.

The models were estimated on the 1st differences, used rolling 1-year (259-day) estimation periods and predicted the expected change in the endogenous variable 1 day ahead. The currency positions were initiated with forward contracts (with swaps used for rolling the position forward if the position stayed the same overnight) and the interest rate positions were initiated with 10-year government bond futures (1 contract in both countries). The models had an ARMA(1,1) setup with seasonal dummies and a constant added as exogenous variables. The setup of the equations was kept constant for the entire test period, in spite of it resulting in some of the coefficients being statistically insignificant during some estimation periods. The statistical properties of the estimated equations for the last 259-day period, the graphs of the models' residuals for the entire test period (the difference between the out-of-sample predicted change for the next period and the actual change) and the tests for the models' residuals normal distribution, autocorrelation and stationarity can be studied Appendix 2.

The curves of the cumulative excess returns from the currency positions are shown in Figure 8 and the performance statistics in Table 9. The excess returns are calculated as a percentage of fixed notional capital in forward contracts and swaps (see also footnote 51). The profits/losses from USD/JPY positions were calculated into euro at the end of each trading day.

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[52] Although the model results are tested from December 31st, 1992, we need the first year of data to calculate the first trading signals.
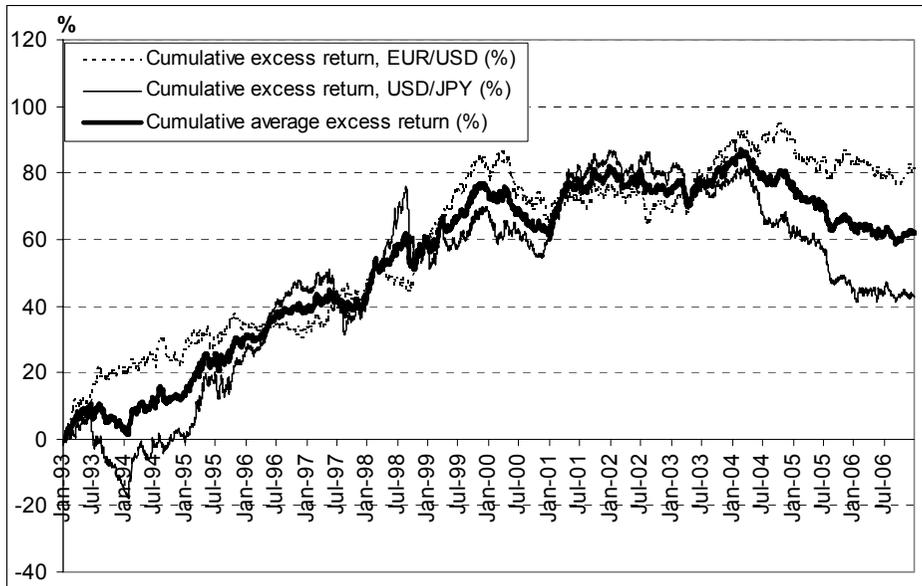
Figure 8. Simulated cumulative excess returns from the USD/EUR and the USD/JPY currency pairs using the ARMA(1,1) setup with seasonal dummies and a constant.

Table 9. Simulated results and selected statistics of the currency positions.

Statistics	Average	USD/EUR	USD/JPY
Cumulative excess return (%)	61.85	81.11	42.59
Average monthly excess return (%)	0.37	0.48	0.25
Standard deviation of average monthly excess return (%)	2.30	2.93	3.32
Sharpe ratio, annualized	0.56	0.60	0.27
Maximum monthly excess return (%)	5.96	9.93	8.68
Minimum monthly excess return (%)	–6.61	–11.45	–12.54
Accuracy	0.52	0.52	0.51
Profit factor	1.10	1.10	1.05
Maximum drawdown (%)	–28.39	–24.01	–45.85
Longest flat period (days)	742	975	1 301
Average yearly excess return (%)	4.42	5.79	3.04

We can see from the figure and the table that for the exchange rate positions the ARMA setup worked a bit better than the tested simple technical strategy based on the crossover of two moving averages. The annualized Sharpe ratio of the entire portfolio was 0.56 and the longest flat period a bit below 3 years, which are both better than the corresponding statistics of the model using the moving average strategy.

At the same time there is a clear distinction between the positive performance until the beginning of 2004 and the negative performance after that, showing the same loss in the predictability of the easier strategies during the last years that can be observed in Olson (2004), Loeys and Fransolet (2004), Normand *et al.* (2004) and from the results of the previously tested moving average model on the same exchange rate pairs. The average monthly excess return from one position was 0.37%, which corresponds to 3 700 euro, if the forward contracts and swaps would have been initiated with a notional amount of 1 million euro.

The curves of the cumulative excess returns from the interest rate positions are shown in Figure 9 and the performance statistics in Table 10. The sizes of the interest rate positions were 1 contract in both countries, which corresponds to a contract value of 100 000 USD and 100 000 euro, respectively. The curve of the average excess return is an arithmetic average of the excess returns from both countries.
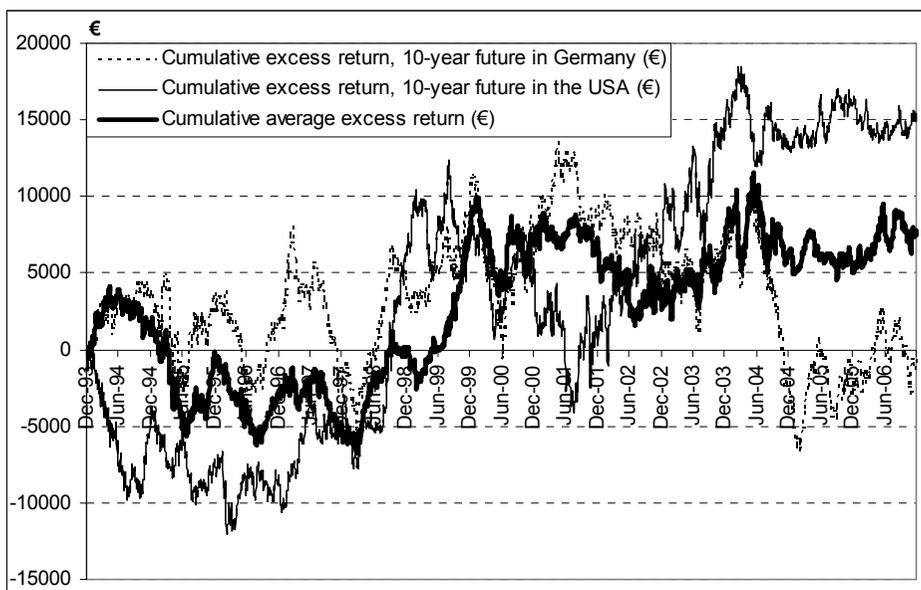
Figure 9. Simulated cumulative excess returns from the 10-year interest rate futures in the USA and Germany using the ARMA(1,1) setup with seasonal dummies and a constant.

Table 10. Simulated results and selected statistics of the interest rate positions.

Statistics	Average	Germany	USA
Cumulative excess return (€)	4 222	–6 930	15 375
Average monthly excess return (€)	25.00	–41.25	91.52
Standard deviation of average monthly excess return (€)	1 162	1 622	1 730
Sharpe ratio, annualized	0.07	–0.09	0.19
Maximum monthly excess return (€)	3 294	3 320	4 934
Minimum monthly excess return (€)	–2 869	–4 280	–4 202
Accuracy	0.51	0.51	0.51
Profit factor	1.01	0.99	1.03
Maximum drawdown (€)	–10 895	–22 450	–17 078
Longest flat period (days)	1 425	1 723	1 452
Average yearly excess return (€)	302	–495	1 098

We can see from the figure and the table that a simple strategy based on ARMA methodology did not work on the interest rate markets – for Germany's 10-year government bond future the strategy even produced a cumulative loss during the period considered. The annualized Sharpe ratio of the interest rate portfolio was only 0.07 and the length of the longest flat period was longer than six years. The average monthly excess return in percentage terms was only 0.025% of the notional capital (the value of the futures' contracts).

The statistical properties (presented in Appendix 7) of the daily excess returns from the two models based on ARMA methodology are similar to the properties of the excess returns from the models based on two moving averages – here the time series of the excess returns also have a leptokurtic, rather than a normal, distribution with a long left tail.

2.4. Estimation of single factor investment models with fundamental inputs

### 2.4.1. Estimation of the foreign exchange model based on risk-adjusted carry

The model uses the methodology where carry (the short-term interest rate differential) is directly divided by FX market volatility (calculated as an annualized standard deviation of the daily returns in any given currency pair

within the last twelve months) as a risk factor. At the end of each month this carry-to-risk ratio was calculated for fourteen liquid currency pairs (both ways; i.e., 28 carry-to-risk ratios altogether): the USD exchange rate against EUR, JPY, SEK, CAD, GBP, NOK, AUD, CHF, NZD and the EUR exchange rate against JPY, SEK, GBP, NOK and CHF. After that, four currency pairs were chosen that had the highest carry-to-risk ratio. The speculative positions were implemented using one-month forward contracts.

In historical simulations, deposit interest rates were used to calculate the one-month forward exchange rate. All positions were held for one month until the next positions were generated by the model. There are no target or stop levels, and the model has no optimized parameters.

The curves of the cumulative excess returns from the currency model as a whole and from individual currency positions are presented in Figure 10 and the performance statistics in Table 11. The excess returns are measured as a percentage of the fixed notional amount (see also footnote 51) of the forward contracts traded.
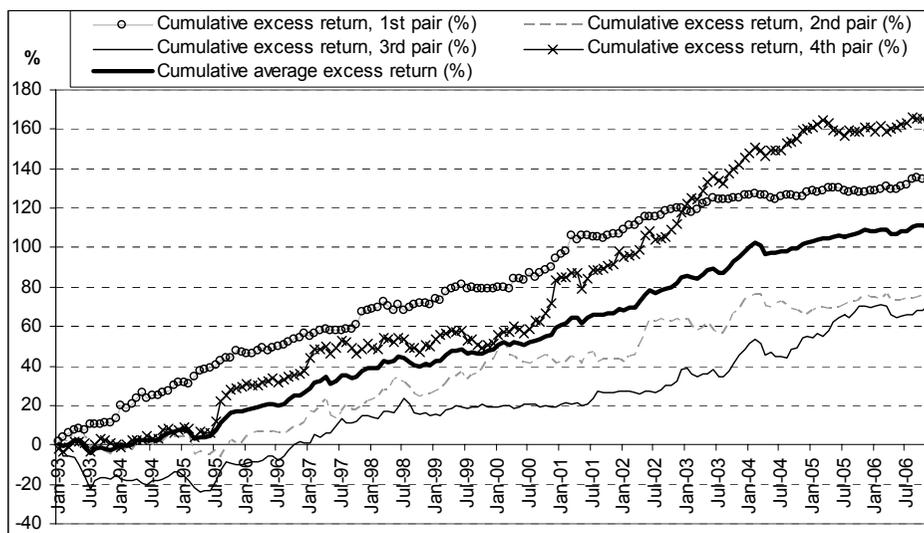
Figure 10. Simulated cumulative excess returns from the currency model using risk-adjusted carry.

As can be learned from the graph, the model based on risk-adjusted carry enables the investor to earn relatively stable excess returns. The annualized Sharpe ratio of the entire model is 1.56 and that of the individual currency pairs between 0.62 and 1.68. Individually, the highest excess returns in the simulations were achieved by the 4th currency pair, followed by the 1st, the 2nd and the 3rd.

The monthly excess returns of individual currency pair positions range from –10.2% to +12.2% and of the entire model from –3.9% to +4.1%. The average monthly excess return in the simulations was 0.7%, the maximum drawdown –6.9%, and the longest profitless period 15 months. These excess returns in percents correspond to an average monthly excess return of 6 700 euro from one position and the range of monthly excess returns from –101 800 euro to +121 700 euro from one position, if the notional size of the forward contracts is 1 million euro.

Table 11. Simulated results and selected statistics of the currency model based on risk-adjusted carry.

Statistics	Average	1st pair	2nd pair	3rd pair	4th pair
Cumulative excess return (%)	113.08	135.98	78.48	73.78	164.07
Average monthly excess return (%)	0.67	0.81	0.47	0.44	0.98
Standard deviation of average monthly excess return (%)	1.50	1.67	2.59	2.21	2.78
Sharpe ratio, annualized	1.56	1.68	0.62	0.69	1.22
Maximum monthly excess return (%)	4.09	8.03	6.67	6.00	12.17
Minimum monthly excess return (%)	–3.91	–3.07	–10.18	–6.17	–7.74
Accuracy	0.73	0.70	0.63	0.58	0.65
Profit factor	3.18	3.95	1.64	1.72	2.54
Maximum drawdown (%)	–6.89	–4.28	–15.97	–24.94	–9.21
Longest flat period (months)	15	9	42	45	16
Average yearly excess return (%)	8.08	9.71	5.61	5.27	11.72

The statistical analysis of the monthly excess returns (see Appendix 7) shows that the hypothesis that the monthly excess returns are normally distributed can be rejected at the 1% significance level, but not at the 5% significance level. If we reject the normality hypothesis, then the kurtosis over 3.6 and negative skewness show that the excess returns have also a leptokurtic distribution with a long left tail, as was the case with the daily returns from the models based on moving averages and the ARMA methodology.

The curve of the cumulative excess return from the currency model based on risk-adjusted carry, divided into two components: the excess return from pure carry[53] (i.e., from earning the interest rate differential) and the excess return from pure exchange rate movements are presented in Figure 11.

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[53] The trading costs are also part of the "carry" component.
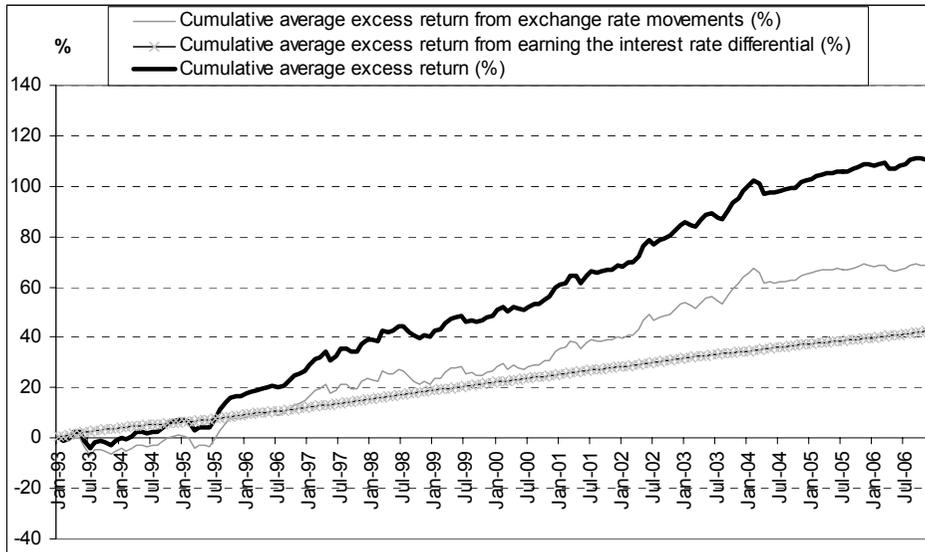
Figure 11. The components of the cumulative excess return from the currency model based on risk-adjusted carry.

The results show that about one third of the cumulative excess return comes from carry and about two-thirds from foreign exchange rate movements. Therefore, it can be concluded that the statement that the omission of interest rate differentials has only a negligible impact on the profitability of currency trading strategies (Olson 2004, p 92 and other quotations presented there) is not correct in longer trading horizons,[54] as a one-third effect to total profitability can by no means be called "negligible." Furthermore, the results also show that the exchange rate movements have been on average in the opposite direction than predicted by the interest rates and forward contracts, showing that the uncovered interest rate parity does not hold.

An attempt was also made to construct and use a risk appetite index based on four indicators: the US 10-year swap spread, the Emerging Markets Bond Index spread, the US High Yield spread and historical foreign exchange market volatility (following JP Morgan 2001 and Kantor and Caglayan 2002). For that, the differences between each risk indicator's value and their 6-month rolling moving average were calculated at the end of each month. Then the "z-scores" were calculated as the ratios of these differences to their 12-month rolling standard deviations. The cumulative risk appetite was calculated as the average of the four indicator's "z-scores." When the risk appetite had a value equal to or

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[54] However, it may be correct if the average length of one trade is sufficiently small – for example, for trading strategies taking intraday positions.

higher than 1.5, then the position for the next month was taken in the opposite way than predicted by the model. The tests indicated that this approach did not improve the cumulative performance of the tested model.

2.4.2. Estimation of a model to capture structural inefficiencies in interest rate markets: long-only duration positions

The goal of the model was to test if the time premium in yield curves can be profitably exploited by simply holding long positions in shorter interest rate or longer government bond futures. The model was tested in the following maturity sectors using the following futures contracts in the following amounts:[55]

- 10-year sector: 10-year government bond futures in the U.S. (8 contracts), Germany (9 contracts), Japan (1 contract), the UK (5 contracts), Canada (11 contracts) and Australia (12 contracts).
- 5-year sector: 5-year government bond futures in the U.S. (11 contracts) and Germany (14 contracts).
- 2–3 year sector: 2-year government bond futures in the U.S. (14 contracts), Germany (34 contracts) and 3-year government bond futures in Australia (27 contracts).
- 1.25-year sector: 5th 3-month interest rate futures contracts in the U.S. (16 contracts), Germany (22 contracts), the UK (24 contracts) and Australia (26 contracts).[56]
- 1-year sector: 4th 3-month interest rate futures contracts in the U.S. (17 contracts), Germany (23 contracts), the UK (25 contracts), Australia (26 contracts) and Canada (10 contracts).
- 0.75-year sector: 3rd 3-month interest rate futures contracts in the U.S. (18 contracts), Germany (25 contracts), the UK (26 contracts), Australia (26 contracts) and Canada (10 contracts).
- 0.5-year sector: 2nd 3-month interest rate futures contracts in the U.S. (22 contracts), Germany (30 contracts), the UK (30 contracts), Australia (29 contracts) and Canada (11 contracts).

For each test the difference-adjusted continuous futures contract was used. The trading costs of rolling over the contract every three months were deducted. As

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[55] The number of contracts was calculated with the goal to have the monthly standard deviation of each individual position at around 13 600 euro. This is the smallest possible monthly volatility that can be achieved by holding Japanese 10-year government bond futures (that have an indivisible contract size of 100 million yen) in the portfolio. The values of the futures' contracts and minimum margin requirements are shown in Table 6.

[56] The 5th contract in Canadian 3-month interest rate future was not included because of its low liquidity.

the overall level of interest rates in all of the covered markets declined during the study period, the positive effect on the simulated performance from the cumulative decline in the interest rate levels was also deducted from the results. The model has no target or stop-loss levels, and the long positions were held for the entire 168-month test period.[57] As the number of different contracts (countries) traded within each maturity sector was unequal, then in order to compare different maturities the averages (and not the sum) of the positions in individual futures of the same maturity sector were compared.

The results of the tests (see Figure 12 for the curves of the cumulative excess return and Table 12 for the performance statistics) indicate that a simple long-only strategy using interest rate futures is indeed capable of profitably exploiting the time premium in yield curves with annualized Sharpe ratios for the shorter durations of between 0.5–0.6. The best performance can be achieved by using the 3rd or the 4th contract of a 3-month interest rate future; the performance of the portfolio of 10-year futures was considerably worse. In addition, it is evident from the figure that all the cumulative excess return series are highly correlated.
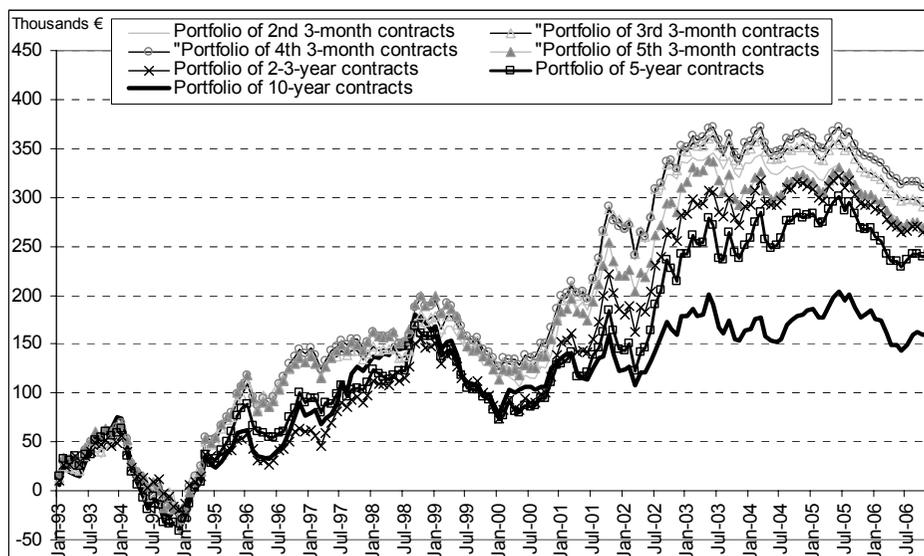
Figure 12. Simulated cumulative excess returns from the long-only positions in government bond and interest rate futures.

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[57] Due to data availability the test period for Germany's 3-month interest rate future begins in July 1994.

Table 12. Simulated results and selected statistics of the long-only positions in government bond and interest rate futures.

Statistics	10-year	5-year	2–3-year	5th 3-month	4th 3-month	3rd 3-month	2nd 3-month
Cumulative excess return (€)	147 963	226 414	253 506	257 433	301 461	282 332	255 041
Average annual excess return (€)	10 569	16 172	18 108	18 388	21 533	20 167	18 217
Average monthly excess return (€)	881	1 348	1 509	1 532	1 913	1 681	1 518
Standard deviation of average monthly excess return (€)	10 467	12 254	10 692	11 082	10 913	10 496	10 355
Maximum monthly excess return (€)	265 441	30 303	26 863	33 844	29 896	29 690	34 375
Minimum monthly excess return (€)	−27 637	−34 087	−26 229	−24 802	−31 037	−31 713	−32 143
Maximum drawdown (€)	−101 766	−104 982	−80 332	−98 555	−99 785	−95 846	−90 695
Sharpe ratio, annualized	0.29	0 38	0.49	0.48	0.57	0 55	0 51
Accuracy	0.57	0.58	0.55	0.55	0.55	0.56	0.52
Profit factor	1.24	1 33	1.44	1.41	1.56	1.52	1 48
Longest flat period (months)	52	36	28	43	42	42	42

In spite of the positive overall performance, the strategy of having long-only positions in interest rate futures had relatively long and steep drawbacks during the test period. The longest flat periods were between 28 and 52 months and the ratios of maximum drawdown to average annual excess return were between 4 and 10 years depending on maturity sector.

The long and steep drawdowns in the performance of the simple long-only portfolios led to the idea of applying a filter to the portfolios that would take the positions off during unfavorable times. Two ideas for constructing the filters were tested: filters based on the shape of the yield curve and filters based on the direction of interest rates.

The yield curve filter was based on the idea that the long futures positions have a higher probability of yielding positive return during the times of steeper upward-sloping yield curves (see also Equation 15). Following this idea, the differences between the interest rate of the underlying securities of the futures contracts and a 1-month deposit interest rate were calculated at the end of each month. If the difference was smaller than a certain threshold, the long futures position was taken off for the next month. Different positive threshold levels were selected and tested for each maturity sector and finally the yield curve spread level, which gave the highest annualized Sharpe ratio for the given maturity sector as a whole, was chosen (see Table 13 for results). In order to get more robust results the tests were carried out with equal threshold levels for all regions within one maturity sector of futures.

Table 13. Optimal threshold levels and return-risk ratios of the portfolios with a yield curve filter.

Statistics	10-year	5-year	2–3-year	5th 3-month	4th 3-month	3rd 3-month	2nd 3-month
Optimal threshold level for yield curve spread (bp)	114	136	70	91	145	112	96
Profit factor	1.81	2.56	1.79	1.87	2.98	2.49	2.87
Sharpe ratio, annualized	0.78	0.88	0.49	0.66	0.72	0.57	0.63

As can be seen from the table, the filter did indeed improve the results of the tested portfolios: the profit factors improved in all maturity sectors and the Sharpe ratios improved in most maturity sectors. The best results were achieved by applying a 136 bp filter to the portfolio of 5-year interest rate futures giving us an annualized Sharpe ratio as high as 0.88 and a profit factor as high as 2.56.

The idea for the second set of filters was to take the long positions off during the times when the general level of interest rates was rising, as the value of the debt instruments decreases when interest rates rise.[58] The base interest rates of

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[58] It can be noted that the drawdown periods of the model (in 1994, 1999 and 2006) coincided with periods of rising base interest rates.

each country were chosen as filters, because these series do not have daily fluctuations. The following simple rule was applied: if the base interest rate level was raised the previous month, then the long position in futures was taken off for the next month. Table 14 shows that the rule increased the risk-return ratios for all positions except the positions in 10-year government bond futures.

Table 14. The return-risk ratios of the portfolios with a base interest rate filter.

Statistics	10-year	5-year	2–3-year	5th 3-month	4th 3-month	3rd 3-month	2nd 3-month
Sharpe ratio, annualized	0.28	0 47	0.58	0.53	0.62	0.64	0.61
Profit factor	1.23	1 44	1.57	1.48	1.61	1.64	1 62

According to the tests, the portfolio of the 3rd 3-month interest rate futures showed the best performance with an annualized Sharpe ratio of 0.64 and a profit factor of 1.64. The curves of the cumulative excess return from the portfolios of 5-year futures with a yield curve filter and the 3rd 3-month futures with a base interest rate filter together with the performance of the two portfolios combined are presented graphically in Figure 13.
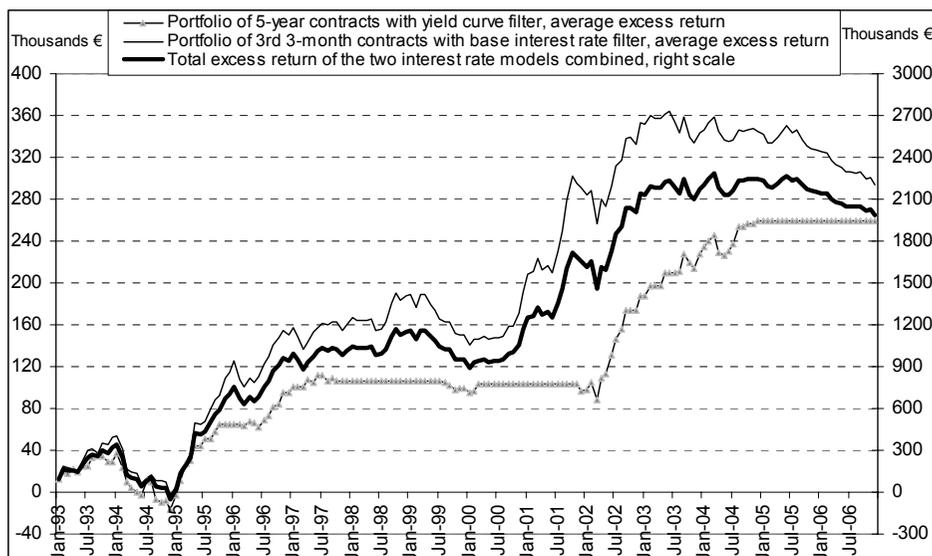
Figure 13. Simulated cumulative excess returns from the portfolios of 5-year futures with a yield curve filter, 3rd 3-month futures with a base interest rate filter and of the portfolio combining the two maturity sectors.

The figure shows that the two series have several periods with similar return (both series had negative return in 1994, positive returns in 1993 and 2002, and almost flat return from 1997 to 2000), but also several periods when they behaved differently; for example, in 2001 and in 2005 – 2006. The annualized Sharpe ratio of the portfolio combining the two interest rate models was 0.74, and had a profit factor of 1.77.

The analysis of the statistical properties of the excess returns from the portfolio of 5-year futures with a yield curve filter shows that the returns have a leptokurtic rather than a normal distribution. At the same time, the hypothesis that the excess returns from the portfolio of 3rd 3-month interest rate futures are normally distributed can not be rejected at the 5% significance level.

2.5. Estimation of multi-factor investment models with fundamental inputs

2.5.1. Estimation of the foreign exchange model with four ranked inputs

The model produces monthly signals to trade three cross-currency positions between ten major currencies (USD, EUR, CAD, CHF, SEK, NOK, JPY, AUD, GBP, and NZD). The signals were obtained by ranking the currencies at the end of each month according to the value of four input variables:[59]

- Deposit interest rate;
- The ratio of the ten-year forward exchange rate to its long-term average**;**
- Monthly change in the 10-year government bond yield;
- Trend indicator.

Therefore, this model differs from the carry-to-risk currency model presented in subchapter 2.4.1 in three aspects – instead of one input four inputs are used, the carry indicator is not divided by a risk measure and instead of 14 currency pairs 45 possible currency pairs are considered.

After ranking the currencies by each input value, the average rank was calculated for each major currency, and then the currencies were ranked by their average ranks.[60] Cross-currency positions were initiated with 1-month forward contracts according to the following rule:[61]

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[59] See a more detailed description of the input variables in subchapter 1.4.2.

[60] Average of each individual rank. In case of parity "a tie breaking rule" was applied that gives more weight to higher individual ranks.

[61] This rule was chosen over the possibilities of buying the 1st currency against all last currencies or the possibility of buying multiple first currencies against only the last currency in order to lower the correlation between the excess returns of traded currency pairs.

- Buy the 1st currency against the 10th
- Buy the 2nd currency against the 9th
- Buy the 3rd currency against the 8th

In historical simulations, deposit interest rates were used to calculate the one-month forward exchange rate. All positions were held for one month until the next positions were generated by the model. There were no target or stop levels,[62] and the model has no optimized parameters. The curves of the cumulative excess return from the currency model as a whole and from the individual currency positions (in percentages of the fixed notional amount of the forward contracts traded,[63] with trading costs deducted) are presented in Figure 14 and the performance statistics in Table 15.
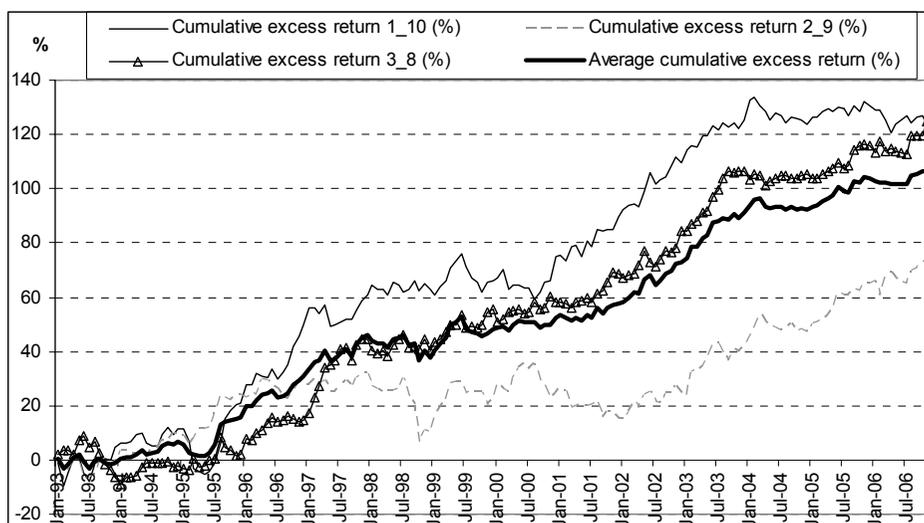
Figure 14. Simulated cumulative excess returns from the currency model.

As can be implied from the graph, the currency model had a relatively good performance in 1995–1997 and 2001–2003, and a more moderate performance in other periods. The statistics of the currency model remain within acceptable ranges: the monthly excess returns of the individual currency pair positions range from –13.3% to +8.9% and of the entire model from –6.1% to +7.1%. The

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[62] Additional research indicated that adding simple stop-loss rules to a currency model does not increase the cumulative results of the model nor reduce the volatility. At the same time, a profit target of around 3.3% to individual positions has a minuscule additional value. The results presented are without a profit target.
[63] See also footnote 51.

average monthly excess return in the simulations was 0.7%, the maximum drawdown –9.4%, and the longest profitless period 18 months.

In absolute terms these results correspond to the average monthly excess return of 6 500 euro with a possible range from – 133 200 euro to +89 000 euro from one currency position, if the notional amount of the forward contracts was 1 million euro. In the results we can also see that the third currency position performed better than the second — a similar result that was also observed in the model based only on risk-adjusted carry, where the highest excess return was achieved by the 4th currency pair. One possible explanation for this phenomenon may lie in the constantly wider use of the speculative currency strategies based on the carry that may cause the currency pairs with the highest carry to lose their excess returns compared to the following, less traded pairs.

Table 15. Simulated results and selected statistics of the currency model.

Statistics	Average	1_10	2_9	3_8
Cumulative excess return (%)	109.52	129.01	73.50	126.06
Average monthly excess return (%)	0.65	0.77	0.44	0.75
Standard deviation of average monthly excess return (%)	1.93	3.29	3.05	2.57
Sharpe ratio, annualized	1.17	0.81	0.50	1.01
Maximum monthly excess return (%)	7.14	8.90	8.58	7.37
Minimum monthly excess return (%)	–6.11	–9.84	–13.32	–5.04
Accuracy	0.68	0.61	0.58	0.68
Profit factor	2.39	1.81	1.47	2.12
Maximum drawdown (%)	–9.36	–17.23	–25.01	–17.45
Longest flat period (months)	18	34	32	32
Average yearly excess return (%)	7.82	9.21	5.25	9.00

The statistical properties of the excess returns from the currency model with four ranked inputs (see Appendix 7) are similar to the properties of the excess returns from the currency model based on a risk-adjusted carry. Here, the hypothesis that the monthly excess returns are normally distributed can also be rejected at the 1% significance level, but not at the 5% significance level. If we do reject the hypothesis of normality, then the kurtosis larger than 4 and a negative skewness shows us that the distribution can be leptokurtic with a long left tail.

The cumulative excess returns of the currency model by single inputs (predictors) are presented in Figure 15. The figure shows possible excess returns

as a percentage of the fixed notional amount of the forward contracts traded, calculated as if this input was the only input used in the monthly ranking.
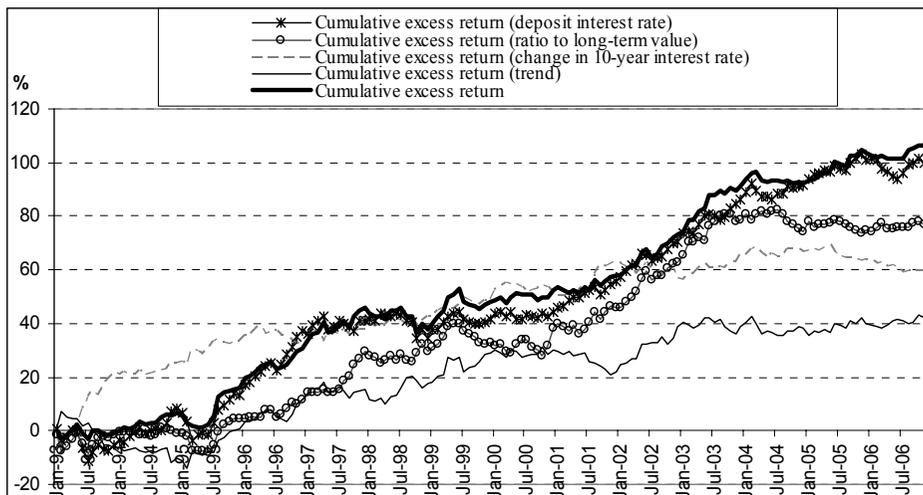
Figure 15. Simulated cumulative excess returns from the currency model by different inputs.

The results indicate that individually, the best predictor is the deposit interest rate. Excess returns from such a single-input model are almost as good as the excess returns from the four-input model. However, the risk statistics (see Vesilind 2006, p 15) of a currency model based only on the deposit interest rate are slightly worse than those of a four-factor model (annualized Sharpe ratios of 0.94 and 1.17, respectively). The other inputs yield weaker, but also positive excess returns when used individually: the annualized Sharpe ratio of a model based only on the ratio of the ten-year forward exchange rate to its long-term average was 0.78 and the annualized Sharpe ratio of a model based only on the change in the 10-year government bond yield was 0.72 in historical simulations. The weakest of the four models is the model based only on the trend indicator with annualized Sharpe ratio of 0.44.

Compared to the currency model based on risk-adjusted carry and described in chapter 2.4.1, the multi-factor model based on ranked inputs has somewhat worse performance statistics in spite of more inputs. The multi-factor model has a lower return, lower Sharpe ratio, lower profit factor and lower accuracy. It also has a larger maximum drawdown and a longer longest flat period than the model based only on risk-adjusted carry. At the same time these two models do not have a stable high positive correlation (see Appendix 4); therefore, using the two models together can give a better overall risk-adjusted performance than

preferring the carry-to-risk model over the multi-factor model and using it alone.

2.5.2. Estimation of the econometric duration model with multiple inputs

The duration model is a regression model that gives monthly signals for the directional trading of the 10-year government bond futures of the USA, Germany and Japan. The model was estimated using the following variables:

- *Endogenous variable*: Excess return of the Citibank 7–10 year government bond index over the 1-month deposit rate. Although the positions are implemented with futures and the results of the model are also based on trading futures, the excess return of the government bond index as an endogenous variable gave better results in ex-post tests than the change in futures prices.

- *Exogenous variables*:
  o *Curve steepness.* The steeper the yield curve (measured as the difference between the 10-year yield and the deposit rate), the higher the return of the 10-year bonds compared to the deposit rate. This is the result of the yield difference and also the result of the expected flattening of the curve.
  o *Real 10-year interest rat.,* Measured as the difference between the 10-year interest rate and the 10-year inflation forecast from the *Consensus Forecasts*. The higher the real interest rate, the higher the probability of decline in interest rates and corresponding increase of return.
  o *Inverted momentum of the stock market as a proxy for economic activity*. Inverted momentum is calculated as the ratio of the six month rolling average of the stock market index to the last value of the stock market index. High inverted momentum indicates declining stock prices and slowing economic activity, which is positive for long-term bonds.
  o *Monthly change in the nominal effective exchange rate (NEER) as a proxy for inflation.* First, a combination of the NEER and commodity price index (CRB index) was tried as a proxy for inflation.[64] Since the CRB index turned out to be insignificant, only the NEER remained in the model. A rising exchange rate lowers inflation and is positive for bonds.

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[64] Conventional inflation measures (CPI, etc.) could not be used, because they are published with a lag.

As all variables in the model have different dimensions and measures, they were normalized[65] before estimation. In order to achieve higher robustness, the coefficients in the equations of the three countries were restricted to being equal to each other. The final model estimated included the following formulas:

$$R_{G,n}=c_1+c_2*CR_{G,n,t-1}+c_3*V_{G,n,t-1}+c_4*CY_{G,n,t-1}+c_5*FX_{G,n,t-1}+c_6*R_{G,n,t-1} \qquad (16)$$

$$R_{U,n}=c_1+c_2*CR_{U,n,t-1}+c_3*V_{U,n,t-1}+c_4*CY_{U,n,t-1}+c_5*FX_{U,n,t-1}+c_6*R_{U,n,t-1} \qquad (17)$$

$$R_{J,n}=c_1+c_2*CR_{J,n,t-1}+c_3*V_{J,n,t-1}+c_4*CY_{J,n,t-1}+c_5*FX_{J,n,t-1}+c_6*R_{J,n,t-1} \qquad (18),$$

where:

R is the excess return of the Citibank 7–10 government bond index over the one-month deposit rate;

CR is the difference between the 10-year government bond yield and the deposit interest rate;

V is the real interest rate calculated using the 10-year government bond interest rate and the 10-year inflation forecast from the *Consensus Forecasts*;

CY is the inverted momentum of the stock market calculated as a ratio of the six month   rolling average of the stock market index to the last value of the stock market index;

FX is the monthly change in the trade-weighted NEER;

G denotes the variable of Germany;

U denotes the variable of the United States;

J denotes the variable of Japan;

n denotes the variable that is normalized before estimation and

$t-1$ denotes the variable at time t-1.

The estimation period for each month was the preceding (rolling) 10-year period.[66] After estimation the endogenous variable for the next month was predicted. Then the rolling estimation "window" was swifted 1 month forward and the estimation of the coefficients was carried out again. The statistics of the model estimated over the last 10-year period, the graphs of the models' residuals for the entire test period (the difference between the out-of-sample predicted change for the next period and the actual change) and the tests for the normal distribution of the models' residuals, autocorrelation and stationarity are shown in Appendix 3.

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[65] First, the observations of the variables were divided by the variable's standard deviation during the estimation period and then the mean of the variable during the estimation period was deducted.

[66] Due to data availability, a small number of first estimations were done with a slightly shorter estimation period.

The forecasted 1-month *ex-ante* signals were tested using difference-adjusted generic futures prices. If the prediction for the next month had a positive sign, then the futures contracts were bought. If the prediction had a negative sign, the futures contracts were sold. All the positions were kept for one month until the model generated new signals. No stops or target levels were used. The curves of the cumulative excess returns from the model trading 10 contracts of US 1-year futures (each having nominal value of 100 000 USD), 10 contracts of German 10-year futures (each having nominal value of 100 000 euro) and one contract of Japanese 10-year futures (with nominal value of 100 000 000 yen) is presented in Figure 16 and the performance statistics in Table 16.[67] The curve of the average return is an arithmetic average of the excess returns from the three countries.
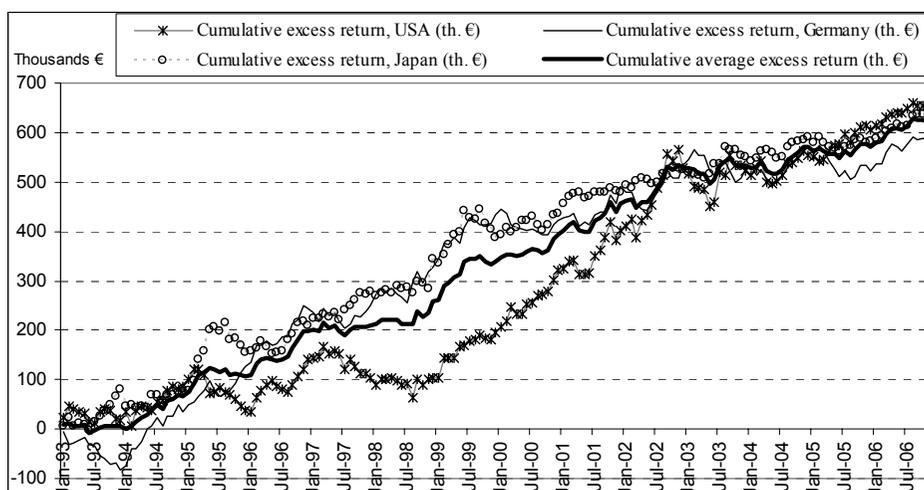
Figure 16. Simulated cumulative excess returns from the duration model.

It can be concluded from the figure and the table above that the overall performance of the entire model was more stable than the performance of its individual instruments. Only the excess returns from the U.S. 10-year futures seem to have three clearly different sub-periods: higher excess returns in 1999–2002 and more moderate excess returns before and after that period. Historical results indicate that the average monthly profit of the three positions together was €11,338 with the results ranging from €–60,220 to €87,242. These absolute values correspond to an excess return of between 0.35 – 0.4% of the total value of the futures' contracts. The minimum margin requirement for the position

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[67] Before 1999, the synthetic euro was used as a proxy for the euro. End-of month exchange rates were used for conversion.

sizes tested is about 27 700 euro,[68] but we can see from the tests that it is more than four times less than the maximum cumulative loss that occurred during the test period. The longest profitless period in the simulation was 12 months, and the biggest drawdown €–111,237.

Table 16. Simulated results and selected statistics of the duration model.

Statistics	Total	Germany	US	Japan
Cumulative excess return (€)	1 904 745	608 900	659 374	636 471
Average monthly excess return (€)	11 338	3 624	3 925	3 789
Standard deviation of average monthly excess return (€)	29 014	15 103	16 809	13 374
Sharpe ratio, annualized	1.35	0.83	0.81	0.98
Maximum monthly excess return (€)	87 242	42 500	60 653	60 229
Minimum monthly excess return (€)	–60 220	–32 100	–40 954	–35 170
Accuracy	0.65	0.60	0.60	0.61
Profit factor	2.78	1.75	1.80	2.14
Maximum drawdown (€)	–111 237	–82 800	–114 089	–60 229
Longest flat period (months)	12	21	29	15
Average yearly excess return (€)	136 053	43 493	47 098	45 462

Different efficiency ratios (Sharpe ratio, accuracy, and profit factor) clearly show the positive effect of diversification. The statistical properties of the monthly excess returns from the duration model (see Appendix 7) show us that the hypothesis that excess returns are normally distributed can not be rejected.

The model was also tested with variable position sizes which were scaled according to the strength of the model signal, but they did not increase si-mulated profits. Additional research also indicated that the addition of different stop-loss, trailing stop or take profit levels does not improve the simulated excess return.

2.5.3. Estimation of the yield curve spread model with multiple inputs

The yield curve positions can be taken in various segments of the yield curve (the short-term part or long-term part) and using various financial instruments:

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[68] If we assume exchange rates of 1.3 USD for 1 euro and 150 JPY for 1 euro.

bond forwards, futures and swaps. In this thesis, a model for taking the 2-year-10-year yield curve spread view using swaps was estimated. The choice was based mostly on the availability of data and on the liquidity of the traded instruments.

The model was estimated for two regions (the USA and Japan) because of data availability. The estimation period for each month was the preceding (rolling) 10-year period. After estimation the endogenous variable for the next month was predicted. Then the rolling estimation "window" was swifted 1 month forward and the estimation of the coefficients was carried out again. The model kept the positions for 1 month according to the sign of the forecast. After that new signals were generated. No stop-loss or target levels were used.

The model used the same variables as the duration model to explain the movements in the 10-year sector. In addition, the change in the monetary policy cycle was added to capture the effect of the monetary policy to the 2-year interest sector. The measure of carry was calculated using the 2-year interest rate instead of the deposit interest rate. As was also the case with the duration model, here the coefficients were restricted to being equal to each other in the equations covering the different countries. The final models estimated had the following form:

$$S_{U,n}=c_1+c_2*CR_{U,n,t-1}+c_3*V_{U,n,t-1}+c_4*CY_{U,n,t-1}+c_5*FX_{U,n,t-1}+c_6*R_{U,n,t-1}+c_7*MP_{U,n,t-1}+ \\ +c_8*S_{U,n,t-1} \qquad (19)$$

$$S_{J,n}=c_1+c_2*CR_{J,n,t-1}+c_3*V_{J,n,t-1}+c_4*CY_{J,n,t-1}+c_5*FX_{J,n,t-1}+c_6*R_{J,n,t-1}+c_7*MP_{J,n,t-1}+ \\ +c_8*S_{J,n,t-1} \qquad (20),$$

where:

S is the change in the yield curve spread calculated as the monthly change in the difference between the 2-year and the 10-year swap interest rates.

CR is difference between the 10-year and the 2-year swap interest rate;

V is the real interest rate calculated using the 10-year government bond interest rate and the 10-year inflation forecast from *Consensus Forecasts*;

CY is the inverted momentum of the stock market calculated as a ratio of the six month rolling average of the stock market index to the last value of the stock market index;

FX is the monthly change in trade-weighted NEER;

MP is the monthly change in the monetary policy, calculated as the ratio of the base interest rate level to its 6-month average;

$_n$ denotes the variable that is normalized before estimation;

$_{t-1}$ denotes the variable at time t-1;

$_U$ denotes the variable of the United States and

$_J$ denotes the variable of Japan.

The statistics of the model estimated for the last 10-year period, the graphs of the models' residuals for the entire test period (the difference between the out-of-sample predicted change for the next period and the actual change) and the tests for the normal distribution of the models' residuals, autocorrelation and stationarity are shown in Appendix 4. Positions during the test period were opened using 1-month forward swap interest rates on the opening date and closed with spot swap interest rates on the close date. The curves of the cumulative excess returns (as a percentage of the fixed notional amount of the swap contracts traded) from this model are presented in Figure 17 and the performance statistics in Tabel 17.
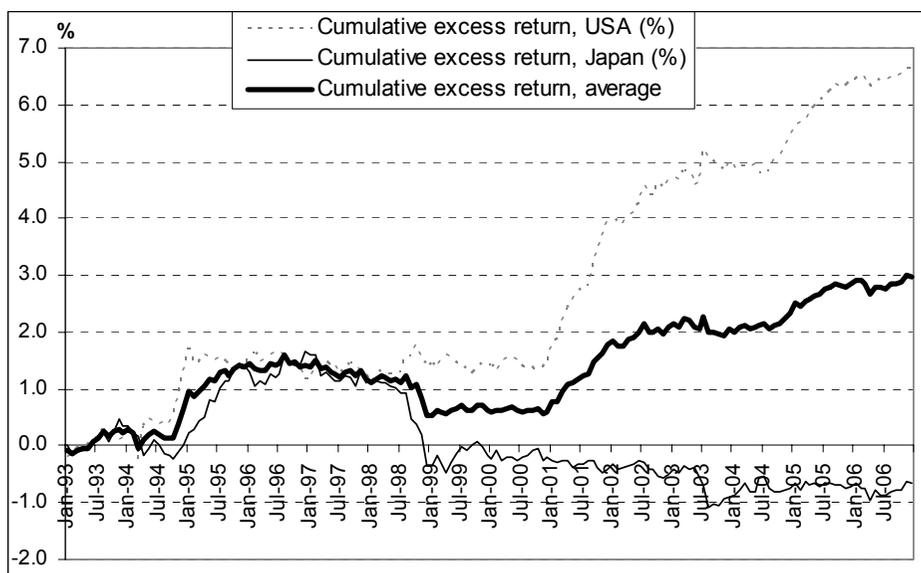
Figure 17. Simulated cumulative excess returns from the yield curve model on swaps.

We can see from the figure and table above that the model worked well (with an annualized Sharpe ratio of 0.92) on US data, but gave a cumulative loss on Japanese data. The excess returns were the highest during the last six years of the test period. The average monthly return from the individual positions was 0.02%, which corresponds to 20 000 euro if the notional amount of the swap contracts was 100 million euro on both the 2-year and 10-year sides.

From the statistical analysis of the monthly excess returns presented in Appendix 7, we can see that the returns have rather a leptokurtic than a normal distribution, with a negative skewness showing a long left tail.

Table 17. Simulated results and selected statistics of the yield curve model on swaps.

Statistics	Average	US	Japan
Cumulative excess return (%)	2.98	6.63	–0.66
Average monthly excess return (%)	0.02	0.04	0.00
Standard deviation of average monthly excess return (%)	0.10	0.15	0.13
Sharpe ratio, annualized	0.64	0.92	–0.10
Maximum monthly excess return (%)	0.31	0.60	0.32
Minimum monthly excess return (%)	–0.32	–0.48	–0.52
Accuracy	0.63	0.65	0.49
Profit factor	1.62	2.14	0.92
Maximum drawdown (%)	–1.06	–0.60	–2.76
Longest flat period (months)	62	44	120
Average yearly excess return (%)	0.22	0.49	–0.04

2.5.4. Estimation of the cross-country yield spread model with four ranked inputs

The model for cross-country yield spread positions is a ranking model that produces monthly signals for taking cross-country yield spread views in 10-year government bonds or corresponding futures. Out of the ten markets considered in this thesis, Switzerland was omitted in this model because of the relative illiquidity of its government bonds (see also Chapter 2.1.2). As the government bonds of Norway and New-Zealand also have relatively high bid-ask spreads, then two models were tested: one having nine markets and taking three monthly positions and one having seven markets and taking two monthly positions.

In six markets (the USA, Germany, Canada, Japan, Australia and the UK) the futures of 7–10 year government bonds were used; in Sweden, Norway and New Zealand's markets 7–10 year government bond indexes were used for back-testing, because liquid futures were not available. In historical back-tests the duration of the two positions in one cross-country pair was assumed to be equal. The currency risk was not hedged as it only influences the final profits and, as a result, is unpredictable and insignificant.

At the end of each month, the nine (seven) markets were ranked applying the same technique as was used in the currency model. The first three explanatory variables were the same as in the duration model and the fourth was a trend reversal indicator:

- *Curve steepness*. Measured as the difference between the 10-year government bond interest rate and the deposit interest rate.

- *Real interest rate.* Measured as the difference between the 10-year government bond interest rate and the latest 10-year inflation forecast.
- *Inverted momentum of stock market.* Used as a proxy for economic activity.
- *Ratio of the 10-year government bond interest rate to its 6-month average*. This is a trend reversal indicator. The higher the current interest rate level is compared to its 6-month average, the higher the probability is that a reversal of trend may occur, raising the price of the corresponding bond/future.

After ranking, the futures (or the 1-month forward contracts of the 10-year government bonds) of the first three (two) regions in the rank were bought and the futures (government bond forwards) of the last three (two) regions in the rank were sold. All the positions were held for 1 month. The model has no target or stop-loss levels and it also has no optimized parameters. At first the comparison was made between the models having seven and nine markets. The most important performance statistics are compared in Table 18.

Table 18. The comparison of the cross-country yield spread models with nine and seven markets.

Statistics	9 markets	7 markets
Average monthly excess return (%)	0.21	0.36
Standard deviation of average monthly return (%)	0.92	1.17
Sharpe ratio, annualized	0.78	1.05
Accuracy	0.65	0.68
Profit factor	1.85	2.38
Maximum drawdown (%)	−6.20	−8.14
Longest flat period (months)	17	18

The results indicate that the benefits from diversification with having nine markets and three monthly positions do not outweigh the additional trading costs that occur with trading Norwegian and New Zealand bonds, as the model with nine markets has a lower excess return, a lower Sharpe ratio, lower accuracy and a lower profit factor than the model with seven markets. Therefore, it was decided to include only seven regions in the final model.

The curves of the cumulative excess return from the final model with seven markets and from individual cross-country spread positions (buy the 1st country against the 7th and buy the 2nd country against the 6th) are presented in Figure 18 and the performance statistics in Table 19. The excess returns are measured as a

percentage of the fixed notional value of the futures' (or forward) contracts traded in each country.
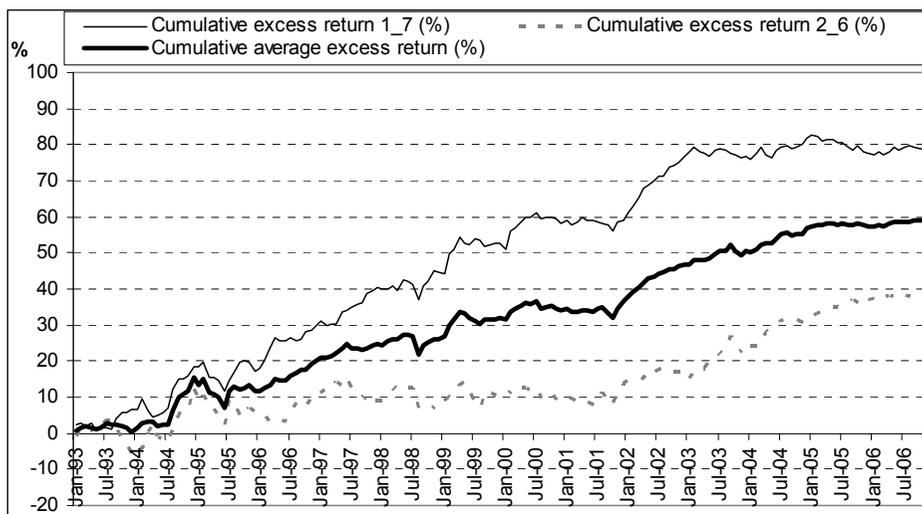
Figure 18. Simulated cumulative excess returns from the cross-country yield spread model.

Table 19. Simulated results and statistics of the cross-country yield spread model.

Statistics	Average	1_7	2_6
Cumulative excess return (%)	59.90	79.66	40.13
Average monthly excess return (%)	0.36	0.47	0.24
Standard deviation of average monthly excess return (%)	1.17	1.55	1.73
Sharpe ratio, annualized	1.05	1.06	0.48
Maximum monthly excess return (%)	4.69	5.10	6.58
Minimum monthly excess return (%)	–4.86	–4.20	–5.52
Accuracy	0.68	0.63	0.61
Profit factor	2.38	2.28	1.46
Maximum drawdown (%)	–8.14	–7.70	–9.89
Longest flat period (months)	18	23	55
Average yearly excess return (%)	4.28	5.69	2.87

According to the back-test, the first cross-country pair performed considerably better than the second pair. At the same time, most of the difference can be attributed to the first half of the test period as later on the performance of both pairs was relatively similar. The efficiency characteristics of the yield spread model are largely similar to those of the currency model. At the same time, the average profit and the volatility of performance in percentage terms are smaller. The average monthly return from the entire model was 0.36% and the results ranged from –4.86% to +4.69%. These percentage values correspond to a monthly excess return of 7 200 euro from the entire model (3 600 euro from individual positions), if the notional value of the positions in each country was 1 million euro. The range of the monthly excess returns from one position in this case was from –55 200 euro to +65 800 euro and from two positions together from –97 200 euro to +93 800 euro. The maximum drawdown of the model was 8.14%, and the longest profitless period was 18 months.

The statistical analysis of the monthly excess returns (see Appendix 7) shows us that the distribution of the excess returns from the cross-country yield spread model has the highest kurtosis (7.1) among all the tested models and the highest Jarque-Bera statistic (120.5) among all the models tested using monthly data. It means that the returns have a leptokurtic distribution and the negative skewness also shows that the returns from this model have a long left tail.

The curves of the cumulative excess return from the cross-country yield spread model by single inputs are shown in Figure 19. The figure shows possible excess returns as a percentage of the fixed notional amount of futures' (forward) contracts traded in each country, calculated as if this input was the only input used in monthly ranking.
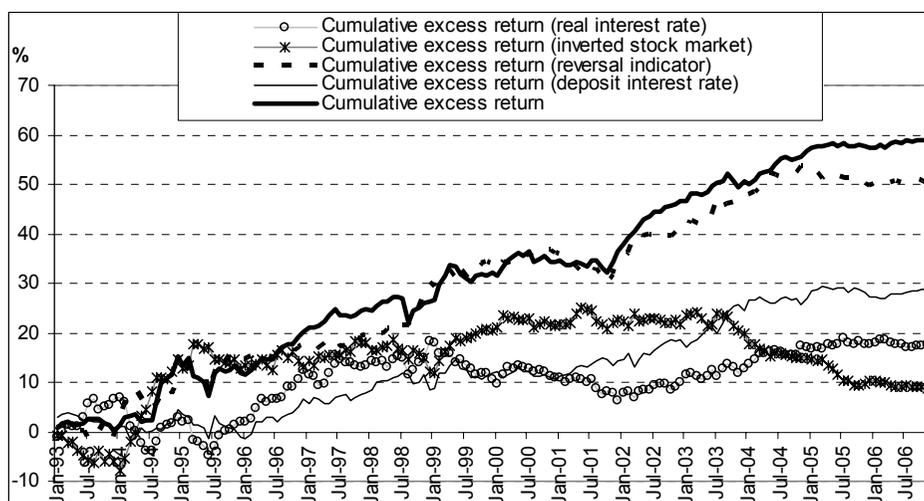
Figure 19. Simulated cumulative excess returns from the cross-country spread model by different inputs.

It can be inferred from the figure that individually the trend reversal indicator is the best predictor (with an individual annualized Sharpe ratio of 0.80) and the inverted stock market performance indicator the worst (with an individual annualized Sharpe ratio of 0.16), especially during the 2nd half of the test period. The model was also tested with three inputs leaving out the inverted stock market index, but the stability of the monthly profits declined. Therefore, all four inputs were retained in the model.

2.6. Creating a single portfolio of separate investment models

2.6.1. Description of the models included, methodologies used and the risk budget

The three portfolio construction methodologies (the traditional portfolio theory, leptokurtic portfolio theory and the naïve portfolio based on fixed weights) included all the models developed in this thesis. The ARMA models were included only in the FX markets, because of their poor performance in the interest rate markets.

- The trend-following model based on the crossover of two moving averages trading USD/EUR and USD/JPY currency pairs;
- The trend-following model based on the crossover of two moving averages trading 10-year government bond futures in the USA and Germany;
- The ARMA model trading USD/EUR and USD/JPY currency pairs;
- The FX model based on risk-adjusted carry trading 4 currency pairs;
- The model having only long duration positions in 5-year government bond futures in the USA and Germany (with a yield curve filter);
- The model having only long duration positions in the 3rd 3-month interest rate futures in the USA, Canada, Great Britain, Australia and Germany (with a base interest rate filter);
- The FX model with four ranked inputs trading 3 currency pairs;
- The econometric duration model trading 10-year government bond futures in the USA, Germany and Japan;
- The econometric yield curve model trading 2-year – 10-year yield curve spreads in the USA and Japan;
- The cross-country yield spread model with four ranked inputs trading two cross-country yield spread positions in the 10-year sector.

Therefore, the entire portfolio included 10 investment models with a total of 27 possible investment positions. Out of those possible 27 positions, 20 of them were always active and 7 positions (the long duration positions in 5-year government bond futures and the 3rd 3-month interest rate futures) also had periods with a neutral investment signal.

As all of the models were tested with different position sizes and different measures (euro versus percentages), then firstly the monthly excess return series from the models were divided by the monthly standard deviations of the excess returns from each model. The resulting excess return series were then included into the combined portfolio with different weights. The weights for the portfolios based on the traditional and leptokurtic portfolio theories were simulated randomly. The weights for the naïve portfolio were calculated with the goal of giving an equal risk budget based on the number of positions traded in each model.

After the simulations, the optimal weights that gave the highest return-to-risk ratio were chosen. Finally, an arbitrary monthly risk budget (the author chose a monthly standard deviation of 1 000 000 euros for the entire portfolio) was used to calculate the actual position sizes based on the optimal weights and to simulate the performance of the entire investment portfolio.

2.6.2. Combining a portfolio based on the traditional portfolio theory

In this thesis the optimal weights were calculated using simulations with the restriction $0<w_i<1$. The efficient frontier of the different portfolios with different weights is shown with a bold line in Figure 20. The figure shows the average monthly excess returns and average monthly standard deviations of the excess returns from the entire portfolio with different simulated weights. The portfolio with the highest annualized Sharpe ratio (2.41) has a monthly standard deviation of the excess returns equal to 1 million euros.
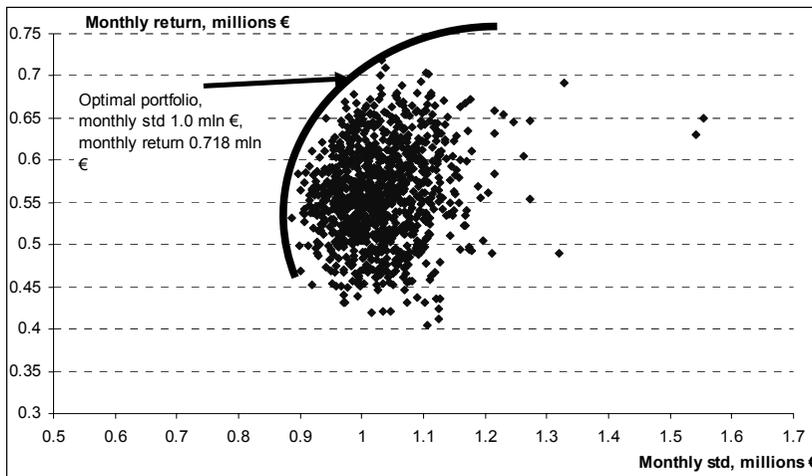
Figure 20. Simulated monthly excess returns from the entire portfolio of models, random weights used in the simulations. The standard deviation was calculated according to the traditional portfolio theory.

Table 20 shows the sizes of the positions in the different models that would have been optimal according to the historical tests based on the traditional portfolio theory:

Table 20. Optimal sizes of the positions for a monthly risk budget of 1 million euro.[69] Calculations based on the traditional portfolio theory. The forex and interest rate (swap and cross-country yield spread) positions are rounded to full thousands.

Model	Notional sizes of the positions
Trend-following FX model	954 000 euro for both USD/EUR and USD/JPY positions
Trend-following IR model	12 contracts of 10-year government bond futures in both regions (the USA and Germany)
ARMA model trading FX	213 000 euro for both USD/EUR and USD/JPY positions
Carry-to-risk FX model	4 FX positions, each with a size of 7 616 000 euro
Long-only duration model, 5-year futures	11 contracts of 5-year government futures in the USA and 14 contracts in Germany
Long-only duration model, 3rd 3-month futures	92 contracts of the 3rd 3-month interest futures in the USA, 128 contracts in Germany, 133 contracts in Great Britain and Australia and 51 contracts in Canada
FX model based on ranked inputs	3 FX positions, each with a size of 4 360 000 euros
Econometric duration model	360 contracts of 10-year government bond futures in the USA and Germany and 36 contracts in Japan
Econometric yield curve model	2 swap positions (one in the USA and one in Japan) with a notional amount of 75 460 000 euros on both the 2- and 10-year sides
Cross-country yield spread model based on ranked inputs	2 cross-country yield spread positions with a total (duration-adjusted positions in two countries together) nominal amount of 12 677 000 euros each

Table 21 shows us the detailed historical performance statistics of the excess returns from the entire portfolio of models and Figure 21 shows us the curves of the cumulative excess returns from the individual models together with the curve of the cumulative excess return from the entire portfolio. The calculations of the excess returns are based on the optimal position sizes presented in the table above.

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[69] Measured as a monthly standard deviation of the excess returns from the entire portfolio of investment models.

Table 21. Simulated results and statistics of the entire portfolio of models. Optimization is based on traditional portfolio theory.

Statistics[70]	Total portfolio
Cumulative excess return (€)	117 185 187
Average monthly excess return (€)	697 531
Standard deviation of average monthly excess return (€)	1 003 861
Sharpe ratio, annualized	2.41
Maximum monthly excess return (€)	3 054 327
Minimum monthly excess return (€)	- 3 135 946
Accuracy	0.77
Profit factor	6.16
Maximum drawdown (€)	−3 555 501
Longest flat period (months)	7
Average yearly excess return (€)	8 370 370
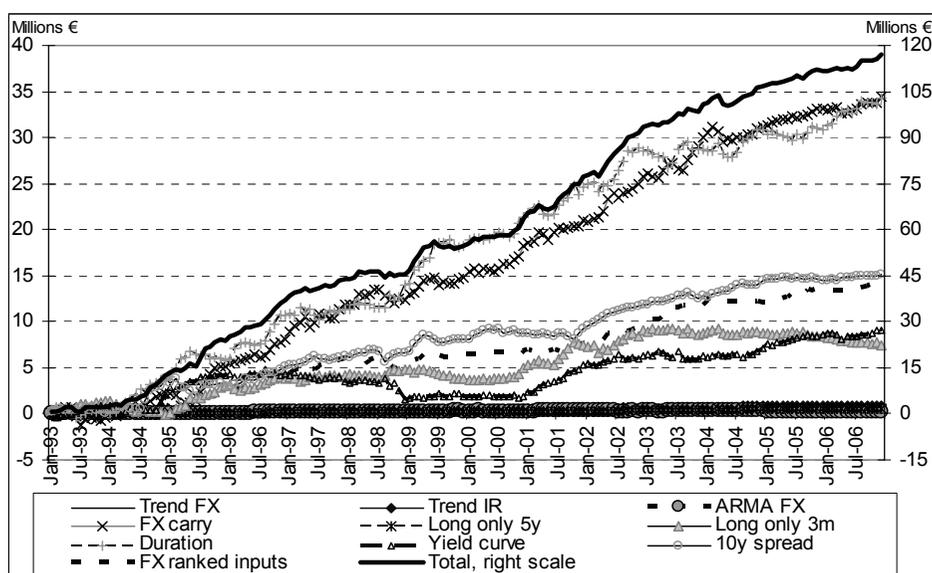
Figure 21. Simulated cumulative excess returns from the entire portfolio of models and from each individual model. Optimization is based on the traditional portfolio theory.

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[70] Note that the standard deviation and the average monthly excess return of the actual simulated portfolio differ somewhat from the theoretical 1 million and 0.718 million euro. The difference is caused mostly by the non-divisibility of the futures' contracts and the rounding of forex positions to full thousands of euro.

We can see from the figure and the table that the performance of the entire portfolio depends mostly on the two models with the highest weights in the simulation: The FX model based on risk-adjusted carry and the econometric duration model. Four more models – the cross-country yield spread model based on ranked inputs, the FX model based on ranked inputs, the econometric yield curve model and the model having long duration positions in the 3rd 3-month interest rate futures make a significant contribution to the overall portfolio. The models based on the crossover of two moving averages, the models based on the ARMA methodology and the duration model in the 5-year government bond futures make only a very marginal contribution to the overall portfolio.

The benefits from diversification can be clearly seen from the statistics with the entire portfolio of models having an annualized Sharpe ratio of 2.41, a profit factor of 6.16 and 77% of the months with positive excess returns. Furthermore, the risk statistics are relatively good with a maximum drawdown exceeding only marginally the minimum monthly return. The statistics show that the optimal portfolio created 0.7 units of average monthly return and 8.4 units of average yearly return for one unit of risk, measured as the monthly standard deviation of the excess returns from the entire investment portfolio.

2.6.3. Combining a portfolio based on the leptokurtic portfolio theory

The framework for analyzing the total portfolio based on the leptokurtic portfolio theory was similar to the framework described in the previous chapter. The only difference was the use of non-kernel covariations in the calculations – i.e., to find the optimal weights only those months when the excess return from at least one model exceeded its monthly standard deviation by 3 or more times were included. Out of 168 months tested 19 months satisfied this criterion.

The efficient frontier of the different portfolios with different weights is shown with a bold line in Figure 22. The figure shows the average monthly excess return[71] and average monthly drawdown risk[72] for different randomly simulated weights and is scaled so that the optimal portfolio would have the same monthly standard deviation as did the optimal portfolio in the analysis using the traditional portfolio theory (i.e., 1 million euro). The portfolio with the highest annualized Sharpe ratio[73] (1.61) has an average monthly excess return of 0.65 million euros and a monthly drawdown risk of 1.40 million euros.

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[71] Average of all months.

[72] Measured as the monthly standard deviation of the entire portfolio of models during the months when at least one model's excess return exceeded its monthly standard deviation by 3 or more times.

[73] A drawdown risk was used instead of a standard deviation.
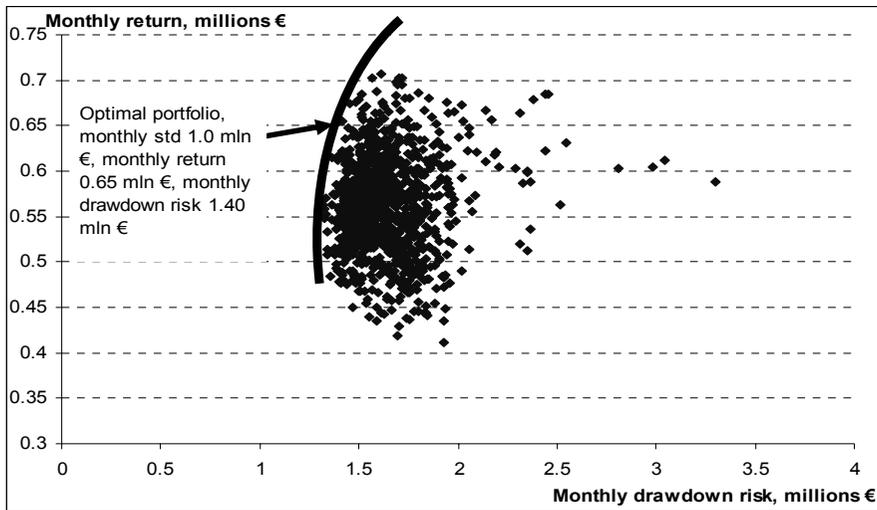
Figure 22. Simulated monthly excess returns from the entire portfolio of models. Random weights were used in the simulations. The drawdown risk was calculated according to the leptokurtic portfolio theory.

Table 22 shows the sizes of the positions of different models that would have been optimal according to the historical tests based on the leptokurtic portfolio theory:

Table 22. The optimal sizes of the positions with a risk budget of 1 million euro.[74] The calculations are based on the leptokurtic portfolio theory. The forex and interest rate (swap and cross-country yield spread) positions are rounded to full thousands.

| Model	Notional sizes of the positions
Trend-following FX model	2 517 000 euro for both USD/EUR and USD/JPY positions
Trend-following IR model	21 contracts of 10-year government bond futures in both regions (the USA and Germany)
ARMA model trading FX	6 986 000 euro for both USD/EUR and USD/JPY positions
Carry-to-risk FX model	4 FX positions, each with a size of 8 808 000 euro
Long-only duration model, 5-year futures	27 contracts of 5-year government futures in the USA and 35 contracts in Germany
Long-only duration model, 3rd 3-month futures	16 contracts of the 3rd 3-month interest futures in the USA, 23 contracts in Germany, Great Britain and Australia and 9 contracts in Canada

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[74] Measured as a monthly standard deviation of the excess returns from the entire portfolio of investment models.

Model	Notional sizes of the positions
FX model based on ranked inputs	3 FX positions, each with a size of 3 787 000 euros
Econometric duration model	252 contracts of 10-year government bond futures in the USA and Germany and 25 contracts in Japan
Econometric yield curve model	2 swap positions (one in the USA and one in Japan) with a notional amount of 112 135 000 euros on both the 2- and 10-year sides
Cross-country yield spread model based on ranked inputs	2 cross-country yield spread positions with a total (duration-adjusted positions in two countries together) nominal amount of 2 158 000 euros each

Table 23 shows the detailed historical performance statistics of the entire portfolio of models and Figure 23 shows us the curves of cumulative excess returns from each individual model together with the curve of cumulative excess return from the entire portfolio. The calculations of the excess returns are based on the optimal position sizes presented in the table above.

Table 23. Simulated results and statistics of the entire portfolio of models. Optimization is based on the leptokurtic portfolio theory.

Statistics	Total portfolio
Cumulative excess return (€)	106 694 749
Average monthly excess return (€)	635 088
Standard deviation of average monthly excess return (€)	989 943
Sharpe ratio, annualized	2.22
Maximum monthly excess return (€)	3 215 758
Minimum monthly excess return (€)	–3 414 201
Accuracy	0.76
Profit factor	5.42
Maximum drawdown (€)	–3 820 191
Longest flat period (months)	9
Average yearly excess return (€)	7 621 053
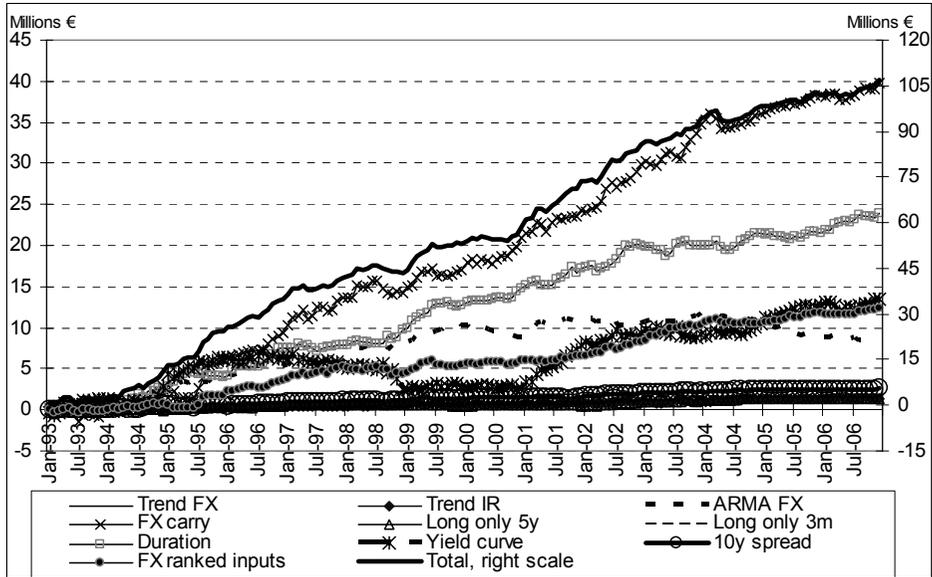
Figure 23. Simulated cumulative excess returns from the entire portfolio of models and from each individual model. Optimization is based on the leptokurtic portfolio theory.

We can see from the figure and table above that the optimal portfolio based on the leptokurtic portfolio theory depends mostly on the two models that also had the highest weights in the portfolio calculated using the traditional portfolio theory: the FX model based on risk-adjusted carry and the duration model. At the same time we can see that the model based on the ARMA methodology makes a much higher contribution and the long duration model in the 3rd 3-month interest rate futures makes only a marginal contribution compared to the weights these models had in the portfolio based on the traditional portfolio theory.

We can also see that although the portfolio optimized based on the leptokurtic portfolio theory should have less drawdown risk, it was not the case in our simulations – the worst month and the maximum drawdown of the leptokurtic portfolio are worse than the corresponding statistics of the portfolio that was optimized based on the traditional portfolio theory. The reason for that may lie in the fact that the hypothesis of normal distribution (in favor of leptokurtic) of the monthly excess returns from one of the two models with the highest weights (the econometric duration model) could not be rejected with any meaningful significance level (p-value 0.57, see Appendix 7). Another reason may be the optimal threshold level for dividing the months into two groups: the months having only a fluctuation risk and to the months also having a drawdown risk (currently 3 standard deviations based on Kitt and Kalda (2006, p 145) and suggested for a portfolio consisting of equities) may not be

appropriate for a portfolio consisting of different investment models for earning excess returns in interest rate and foreign exchange markets.

2.6.4. Combining a naïve portfolio based on the number of instruments traded

In addition to the two theoretically optimized portfolios a simpler, un-optimized portfolio was also tested for comparison. It gave each model a risk budget (measured as the monthly standard deviation of the excess returns of the model) proportional to the amount of the instruments traded in the given model: volatility x to a model trading 1 instrument, volatility 2x to a model trading 2 instruments and volatility nx to a model trading n instruments.

Table 24 shows the sizes of the positions of the different models based on above-described simple setup:

Table 24. The sizes of the positions based on the number of instruments the model trades.

Model	Notional sizes of the positions
Trend-following FX model	3 801 000 euro for both USD/EUR and USD/JPY positions
Trend-following IR model	56 contracts of 10-year government bond futures in both regions (the USA and Germany)
ARMA model trading FX	3 652 000 euro for both USD/EUR and USD/JPY positions
Carry-to-risk FX model	4 FX positions, each with a size of 5 608 000 euro
Long-only duration model, 5-year futures	154 contracts of 5-year government futures in the USA and 196 contracts in Germany
Long-only duration model, 3rd 3-month futures	158 contracts of the 3rd 3-month interest futures in the USA, 220 contracts in Germany, 229 contracts in Great Britain and Australia and 88 contracts in Canada
FX model based on ranked inputs	3 FX positions, each with a size of 4 355 000 euros
Econometric duration model	174 contracts of 10-year government bond futures in the USA and Germany and 17 contracts in Japan
Econometric yield curve model	2 swap positions (one in the USA and one in Japan) with a notional amount of 43 466 000 euros on both the 2- and 10-year sides
Cross-country yield spread model based on ranked inputs	2 cross-country yield spread positions with a total (duration-adjusted positions in two countries together) nominal amount of 7 172 000 euros each

Table 25 shows us the detailed historical performance statistics of the entire portfolio of models and Figure 24 shows us the curves of the cumulative excess returns from each individual model together with the curve of cumulative excess return from the entire portfolio of models. The calculations of the excess returns are based on the fixed naive position sizes presented in the table above.

Table 25. Simulated results and statistics of the entire portfolio of models. Optimization is based on the number of instruments traded.

Statistics	Total portfolio
Cumulative excess return (€)	101 220 181
Average monthly excess return (€)	602 501
Standard deviation of average monthly excess return (€)	997 056
Sharpe ratio, annualized	2.09
Maximum monthly excess return (€)	3 412 484
Minimum monthly excess return (€)	−3 227 690
Accuracy	0.73
Profit factor	5 08
Maximum drawdown (€)	−3 911 475
Longest flat period (months)	9
Average yearly excess return (€)	7 230 013
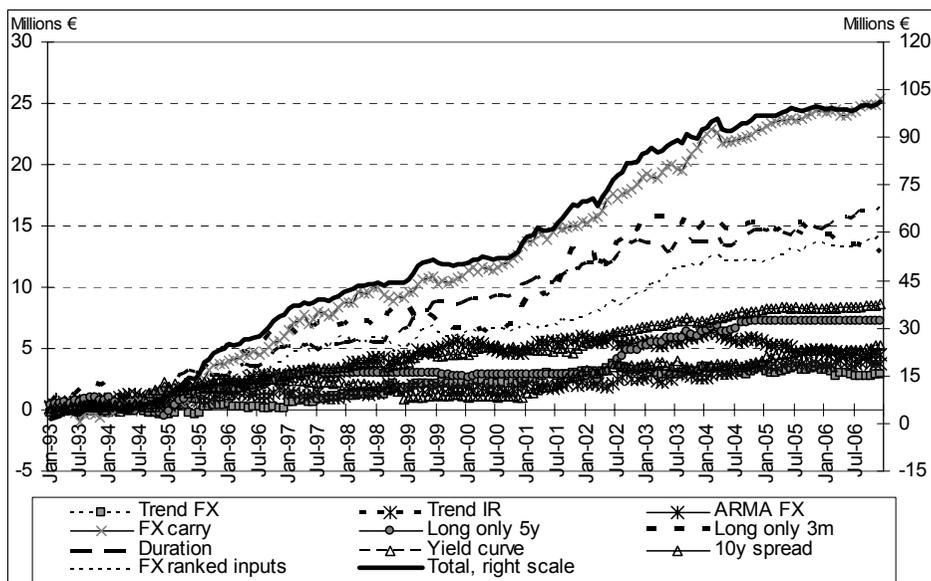
Figure 24. Simulated cumulative excess returns from the entire portfolio of models and from each individual model. Optimization is based on the number of instruments traded.

We can see from the figure and the table above that the portfolio based on the number of instruments each model trades has somewhat worse performance statistics (Sharpe ratio, profit factor and accuracy) than the portfolios based on the traditional and the leptokurtic portfolio theories. At the same time, the drawdown statistics (maximum drawdown and minimum monthly excess return) are comparable to the corresponding statistics of the portfolio based on the leptokurtic portfolio theory. We can also see that the contribution of the individual models to the performance of the total portfolio is more similar than it was in the portfolios based on the portfolio theory. At the same time, the two models that make the biggest contribution – the FX model based on risk-adjusted carry and the duration model – remained the same.

### 2.6.5. Comparison of different portfolio combination methodologies

The comparison of the three tested portfolio combination methodologies is shown in Table 26 and Figure 25. The sizes of the positions are the same as they were in the individual tests. All three portfolios have a risk budget (monthly standard deviation of the excess returns) as close to 1 million euros as is possible considering the non-divisibility of the futures contracts and the rounding of the FX positions and the interest rate positions traded with swaps.

We can see from the figure and the table above that the portfolio weighted based on the leptokurtic portfolio theory is clearly inferior to the portfolio based on the traditional portfolio theory. However, the differences between the two portfolios are relatively small and can be caused by chance or a relatively high threshold level (3 standard deviations resulting in only 19 months fulfilling the criteria) for defining the months to be included in the calculation of the weights for the model based on the leptokurtic portfolio theory.

If we look only at the performance statistics, then we can also conclude that the portfolio based on the number of instruments traded is inferior to the portfolio based on the traditional portfolio theory. At the same time, the portfolio based on the number of instruments traded is not optimized using the historical correlations between the results of the different models and can subsequently be more robust in the future if the correlations change.

Table 26. Comparison of the performance statistics of the three tested portfolios.

Statistics	Portfolio combined based on …		
	the traditional portfolio theory	the leptokurtic portfolio theory	the number of instruments each model trades
Cumulative excess return (€)	117 185 187	106 694 749	101 220 181
Average monthly excess return (€)	697 531	635 088	602 501
Standard deviation of average monthly excess return (€)	1 003 861	989 943	997 056
Sharpe ratio, annualized	2.41	2.22	2.09
Maximum monthly excess return (€)	3 054 327	3 215 758	3 412 484
Minimum monthly excess return (€)	–3 135 946	–3 414 201	–3 227 690
Accuracy	0.77	0.76	0.73
Profit factor	6.16	5.42	5 08
Maximum drawdown (€)	–3 555 501	–3 820 191	–3 911 475
Longest flat period (months)	7	9	9
Average yearly excess return (€)	8 370 370	7 621 053	7 230 013
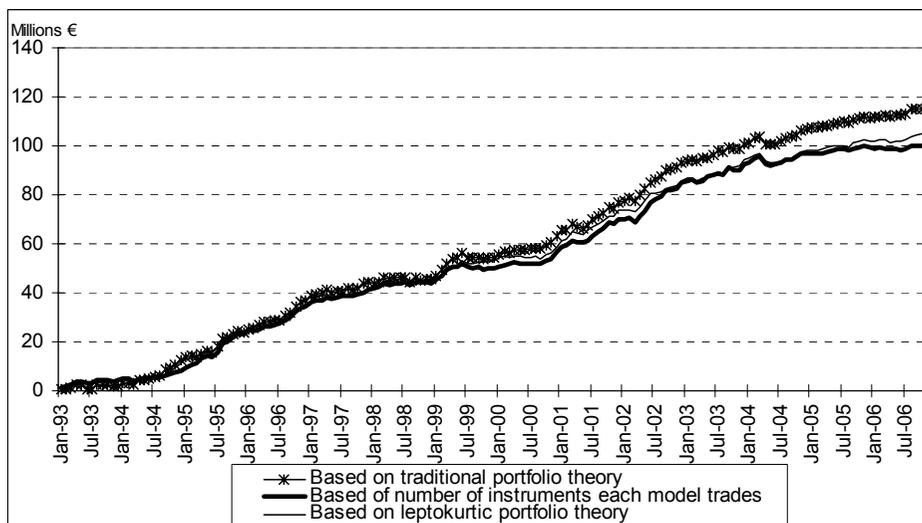
Figure 25. Cumulative excess returns of all three simulated portfolios.

To assess the possible spurious effect of using past historical correlations, the rolling 12-month correlations between all models tested were calculated. The results are shown in Appendix 5. We can see from the figures that the rolling correlations are relatively unstable. Therefore, we can conclude that the positive effect on the simulation results from using past actual correlations can be relatively high. In addition, it was tested if the portfolio based on the portfolio theory yields statistically significant superior returns compared to the naive portfolio based on the methodology proposed in White (2000) and also taking into account the possible biases. The test of the null hypothesis, if the superior return is negative or equal to zero yielded a naïve p-value of 0.18. As the naïve p-value was already statistically insignificant, then there was no need to calculate the Reality Check p-value that also controls for the data mining bias.

Therefore, we can conclude that it would be equally reasonable to use simpler and un-optimized naïve portfolio construction methods (for example, based on the number of instruments traded) instead of the portfolio theory, as the differences in the simulated performance results of the portfolios based on the portfolio theory and based on naïve weights are not statistically significant.

The results of the entire investment portfolio show us that the excess returns from the entire portfolio are stable enough for actual implementation and that diversifying the investment portfolio between different markets and between different classes of models (models using only price data vs. models using economic inputs and models using only one input vs. multi-factor models) improves the risk-return ratio of the entire portfolio significantly. The annualized Sharpe ratios in excess of 2 show that the entire portfolio of models can earn positive excess returns in a one-year time horizon with a high statistical significance.

The results of the tested portfolios are better than the previous attempts to combine multiple investment models (MacMahon (2004) with an information ratio of 1.14, and models by Ilmanen and Sayood (2002) and Ilmanen *et al* (2002) with information ratios of around 1.5), better than the median performance of active currency overlay managers and the median performance of all active managers (with an annualized Sharpe ratio of 0.5), the median performance of active global emerging market debt and of active global equity managers (with an annualized Sharpe ratio of 0.4) and of active global fixed income hedge funds (with an annualized Sharpe ratio of 0.2) (the data for comparison is taken from Collins et al. 2005, p 76). The annualized Sharpe ratio of the excess returns from the portfolio developed in this thesis is also about 8 times higher than the Sharpe ratio of the excess returns achievable by investing in the S&P 500 equity index instead of US 1-month deposit interest rate (0.27, author's calculations, data from 1934 to 2006).

CONCLUSIONS

This thesis consists of two chapters. The first chapter develops a theoretical methodology for earning excess returns in global debt and currency markets with active investment strategies. First, the existence of minute inefficiencies in the financial markets is discussed using the concept of rationally efficient markets (Grossman and Stiglitz 1980). Then the possibilities of earning excess returns with active investment strategies in different asset classes (equities, bonds and foreign exchange) are compared. Finally, the concept of diversification is introduced and the experience from previous studies is analyzed. The chapter concludes with a theoretical framework for estimating a portfolio of active investment models that take investment positions in interest rate and foreign exchange markets of ten major economic areas.

In the second chapter the active investment models are estimated and their historical performance during a 14-year long period is tested. The models (trading strategies) are tested using derivative instruments (futures, forwards and swaps), thus allowing for a clear distinction to be made between the results of passive and active investment decisions. The chapter concludes with a comparison of the three methodologies for combining the estimated models into one portfolio: the first is based on the traditional portfolio theory, the second is based on the leptokurtic portfolio theory and the third is based on the number of different instruments each model trades.

Theoretical framework for estimating a diversified portfolio of active investment models for taking active risk in interest rate and foreign exchange markets

The development of profitable active investment strategies in the interest rate and foreign exchange markets is based on three theoretical assumptions:

1. The "rational efficient market formulation" theory (Grossman and Stiglitz 1980) states that for the financial markets to be in equilibrium there has to be an "equilibrium amount of disequilibrium" in the markets. This means that the markets can not be fully efficient and the investors who invest their time and effort seeking small inefficiencies in the markets should be (and are) rewarded for their time and effort with higher gross returns. The rewards should be higher for the investors using derivative instruments for taking active investment

positions, because the share of trading costs in absolute profit/loss is the smaller when a higher leverage is used.

2. The assumption that interest rate and foreign exchange markets are, on average, less efficient than the equity markets. This assumption is based on the relative importance of investors with return being their most important goal in these markets. While the most important goal of equity investors is usually return, this is not the case with many participants in the interest rate and foreign exchange markets. For example, for central banks when they set short-term interest rates for monetary policy goals, for the countries who invest their excess national reserves abroad the main goal of which is not often the return but the preservation of the capital, and for the companies who trade internationally and want to manage the exchange risk on the costs of their inputs and on the revenues from items sold (Collins et al. 2005, Rozanov 2004, Dales and Meese 2003 etc).

3. With diversification between different inputs, modeling techniques and market segments, the small existing inefficiencies in different markets can be exploited together and the performance of an entire portfolio of diversified active investment models may be stable enough to be used in actual trading (McMahon 2004, Ilmanen and Sayood 2002, Clarke *et al.* 2002, etc).

Based on the above-described assumptions, a theoretical portfolio of active investment models is developed in this thesis. The portfolio consists of the following approaches that have also been successfully used in previous studies on active investment models:

1. Models that use only the past observations of the financial time-series itself as inputs. Both simple models based on technical analysis and simple univariate econometric models are tested in both the interest rate and foreign exchange markets.

2. Models that are based on structural risk premiums in the foreign exchange and interest rate markets. These models are based on empirical findings that the uncovered interest rate parity on average does not hold in foreign exchange markets and that the time expectations theory performs relatively poorly in describing the movements in the yield curves.

3. Models that are based on the ranking of different markets on the basis of the ranking of different input variables and take investment positions according to the rule "buy the 1st against the last, the 2nd against the second-to-last, etc." Both a model for foreign exchange positions (covering ten major currencies) and a model for cross-country 10-year yield spread positions (covering the seven most liquid bond markets) are tested.

4. Models where investment signals are based on econometric multi-variate models. These models are applied for taking duration and yield curve spread positions.

After the estimation of the individual models, the models are combined into a single portfolio to test the validity of the Law of Active Management. Three portfolio combination methodologies are used: the first is based on the traditional portfolio theory, the second is based on the leptokurtic portfolio theory and the third is based on simply the number of the instruments each model trades. The simple combined portfolio with weights proportional to the number of the instruments traded acts as a benchmark. The results of the combined portfolio based on the portfolio theory are compared to the benchmark portfolio to see if the improvement of the results achieved by including historical correlations and portfolio optimization are large enough to be statistically significant considering thealso possible over-optimization that can arise from using historical correlations in the calculations. The goal of testing the portfolio that is combined based on the leptokurtic portfolio theory is to see if the leptokurtic portfolio theory enables investors to attain a portfolio that would have less drawdown risk than the portfolio combined by the traditional portfolio theory.

Research methodology and data

All the models are estimated and tested during a 14-year (168-month) test period starting on December 31, 1992, and ending on December 31, 2006. All the models are implemented using derivative instruments: futures, swaps or forwards. In this way the results of the estimated models reflect pure excess return that can be earned over a pre-determined benchmark: the funds invested according to the pre-determined benchmark can act just as collateral for the derivative portfolio as long as they are invested in liquid financial instruments (money-market instruments, deposits, etc.). Furthermore,, the use of derivative instruments enables the investor to minimize foreign exchange risk while taking interest rate views (as the positions are opened and closed to the same value date, then foreign exchange movements have effect only on the profits and losses of the positions, but not on the underlying nominal amount) and enables investors to scale the risk exactly according to their risk tolerance level.

The following descriptive statistics are calculated for each model and later for the entire portfolio:
- Return statistics:
  - Cumulative excess return over the test period.
  - Average annual excess return.
  - Average monthly excess return.
- Risk and volatility statistics:
  - Standard deviation of the average monthly excess return.

- o Maximum monthly excess return.
- o Minimum monthly excess return.
- o Maximum drawdown.
- Different return and risk ratios and lengths of drawback periods:
  - o Annualized Sharpe ratio.
  - o Accuracy.
  - o Profit factor.
  - o Longest flat period.

All historical tests include estimated trading costs taken from actual quotes from institutional trading platforms and/or corresponding exchanges.

The models based on technical analysis use a simple strategy that generates investment signals based on the crossover of two moving averages with different lengths. This model is applied to two currency pairs (USD/EUR and USD/JPY) and to two interest rate markets (10-year government bond futures in the USA and Germany). The same markets are used in a univariate econometric model that uses the ARMA(1,1) setup with seasonal dummies and a constant added as exogenous variables.

The models that are based on structural risk premiums in foreign exchange markets are tested on the 14 most liquid currency pairs (major currencies against the USD and EUR). The model uses the difference between short-term interest rates (carry) divided by the volatility of the FX pair as a risk factor as an input and each month takes the four currency positions that have the highest risk-adjusted carry. The models that are based on the structural time premium in interest rate markets take long positions in the 3rd 3-month interest rate futures and in 5-year government bond futures. In order to avoid losing positions in unfavorable market conditions additional filters are applied to the strategy: a filter based on the direction of the monetary policy cycle to the strategy that trades in the 3rd 3-month futures and a filter based on the steepness of the yield curve to the strategy that trades 5-year futures.

The currency model that is based on the ranking of different inputs uses the deposit interest rate, the ratio of the exchange rate to its long-term average, the monthly change in the 10-year government bond yield and a trend indicator as inputs. The input variables for the model for cross-country 10-year yield spread positions based on the same ranking methodology are: curve steepness, real interest rate, the inverted momentum of the stock market and the ratio of the 10-year interest rate to its long-term average.

The multivariate econometric model for duration positions takes monthly positions in 10-year government bond futures in the USA, Germany and Japan. The model uses simple least-squares regression analysis with the coefficients on the input variables restricted to being equal to each other across different countries to achieve higher robustness. The input variables are the steepness of the yield curve, the real interest rate, the inverted momentum of the stock

market and trade-weighted NEER. The yield curve spread positions are tested on swaps and two regions (the USA and Japan) are included. The input variables are the same as in the duration model, with a variable describing the direction of the monetary policy added to better capture the movements at the short end of the yield curve.

The data sources used in all models and markets were Bloomberg, Reuters EcoWin and *Consensus Forecasts*.

Empirical results of estimated models and practical suggestions

The empirical results showed that the majority of approaches tested gave relatively good and stable investment results according to historical tests. In this way the results confirmed the assumptions that inefficiencies do exist in the foreign exchange and interest rate markets – inefficiencies that can be profitably exploited over longer periods of time.

Historically, the best results were achieved by the foreign exchange model based on risk-adjusted carry. This model had an annualized Sharpe ratio as high as 1.56 and profit factor as high as 3.18 in the simulations. Annualized Sharpe ratios greater than or equal to 1 were also achieved by other models: the econometric duration model (annualized Sharpe ratio of 1.35), the cross-country 10-year yield spread model based on ranked inputs (annualized Sharpe ratio of 1.05) and the currency model based on ranked inputs (annualized Sharpe ratio of 1.17). The worst multi-factor model was the econometric yield curve spread model with annualized Sharpe ratio of 0.64 and profit factor of 1.62.

Relatively weaker results were achieved by simpler models based on past price data and on the structural inefficiencies in the interest rate markets. The model based on the crossover of two moving averages with different lengths had an annualized Sharpe ratio of 0.33 in the foreign exchange market and an annualized Sharpe ratio of 0.50 in the interest rate market. The performance of the model based on the ARMA(1,1) setup had better results in the foreign exchange market (annualized Sharpe ratio of 0.56), but it had the worst result of all in the interest rate market (annualized Sharpe ratio of only 0.07). The common factor among the estimated moving average and ARMA models on foreign exchange rates was their tendency to sharply lose their performance after about 2002 – 2003. This result confirms the results reported by Olson (2004), Loeys and Fransolet (2004) and Normand *et al.* (2004) on the loss of predicting power of simpler (technical) models.

The annualized Sharpe ratios of the interest rate models based on the structural time premium were 0.88 for the 5-year futures sector and 0.64 for the 3rd 3-month futures sector, respectively. Also these models showed declining profitability during the last years, but the reason for that was more likely the

global rise in interest rate levels than the decline in the profitability of simpler technical rules pointed out in the previous paragraph.

The analysis of the statistical properties of the excess returns from the tested models revealed to us that only for the excess returns from the duration model was the hypothesis of normal distribution not rejected. The hypothesis of normality was rejected at the 10% significance level for the excess returns from the long-only interest rate model tested on a portfolio of 3rd 3-month interest rate futures, at the 5% significance level for the excess returns from the two monthly currency models and at the 1% significance level for the excess returns from all of the other tested models. The distributions of the excess returns from all the tested models had a kurtosis larger than 3, indicating that the returns had a leptokurtic distribution. The majority of the models also produced excess returns with a distribution having a long left tail.

The three portfolio combination methodologies tested confirmed the Law of Active Management, as all of the combined portfolios had better risk-return statistics than any individual model. The portfolio that was combined in a very simple and un-optimized way – giving each model a risk amount based on the number of instruments it trades – had a combined annualized Sharpe ratio of 2.09 and profit factor of 5.08. The portfolios combined using leptokurtic and traditional portfolio theories had even better results (annualized Sharpe ratios of 2.22 and 2.41 and profit factors of 5.42 and 6.16, respectively), but these results were achieved by using correlation data during the test period and the improvement of the performance achieved using portfolio theories was statistically insignificant compared to the naïve portfolio.

The performance statistics of the excess returns from the portfolio of quantitative investment models presented in this thesis are better than the results of previous attempts to combine multiple investment models (MacMahon 2004 with an information ratio of 1.14, and models by Ilmanen and Sayood 2002 and Ilmanen *et al* 2002 with information ratios of around 1.5), better than the median performance of active currency overlay managers and the median performance of all active managers (annualized Sharpe ratio of 0.5), the median performance of the active global emerging market debt and of active global equity managers (annualized Sharpe ratio of 0.4) and of the active global fixed income hedge funds (annualized Sharpe ratio of 0.2) (the data for comparison is taken from Collins et al. 2005, p 76). The annualized Sharpe ratio of the excess returns from the portfolio developed in the thesis is also about 8 times higher than the annualized Sharpe ratio of the excess returns achievable by investing in the S&P 500 equity index instead of the US 1-month deposit interest rate (0.27, author's calculations, data from 1934 to 2006).

The tests on different portfolio combination methodologies had one more interesting result – although the leptokurtic portfolio theory should give us an optimal portfolio with less drawdown risk than a portfolio combined according to the traditional portfolio theory, the results did not confirm that. The deeper

study into the reasons for such an outcome was left for further research. However, two possible causes were given: the failure to reject the hypothesis of normal distribution of the excess returns from the econometric duration model (one of the biggest contributors to the overall portfolio) and the possibility that the threshold level for dividing the test period into months with and without a drawdown risk taken from previous studies on equity markets might have been inappropriate for applying to a portfolio of investment models.

From the empirical results, we can see that a portfolio made up of different weakly correlated active investment models that take active investment positions in the interest rate and foreign exchange markets can be a good addition to many investor's investment portfolios. The annualized Sharpe ratios in excess of 2 show that the entire portfolio of models can earn positive excess returns in a one-year time horizon with high statistical significance.

With a good return-to-risk ratio and a low expected correlation to the real-money investment portfolios consisting of long positions in equities and/or bonds, the active strategies should improve the overall return – risk ratio of the entire investment portfolio of an investor. In order to achieve the best risk control, the active positions can be traded, budgeted and measured separately from the passive real-money portfolio. In this way, the existing investment portfolio's return is not effected by a larger amount than is needed to cover possible losses from active derivative positions. The profits from derivative positions can just be added to the real-money investment portfolio.

Recommendations for future research and additional information

The diversified portfolio of active investment models developed in this thesis can be further diversified in various ways. Within the framework described in the thesis we can add additional markets until the benefits of diversification from added markets stay higher than the additional costs incurred by trading in less liquid markets.

The portfolio of active investment models can also be improved by improving the models tested in the thesis, as some of the models (for example, the models based on the two moving averages or on a simple univariate ARMA setup) have a relatively simple setup with relatively weaker results. In addition, the multi-factor models tested in this thesis did not include all of the possible input variables described in chapters 1.4–1.5. For example, the role of capital flows, investors' positions and market sentiment, market volatility and other measures of risk appetite, and the prices of different commodities can be additional useful predictors in foreign exchange markets.

Additional information can also be found by breaking down the simulation period into shorter sub-periods (sub-periods of high and low volatility, sub-periods of positive or negative directional signals, sub-periods of falling vs.

rising markets, etc.) and analyzing the performance (and the differences in the performance) of the models during these various sub-periods. The question of why the portfolio of the models combined using the leptokurtic portfolio theory did not have the lowest drawdown risk compared to the other tested portfolios also deserves further research.

Moving further from the models tested in this thesis, the entire portfolio of models can be further diversified by the inclusion of models with shorter (for example, intraday) trading horizons, models that trade in different risk classes (for example, volatility, credit risk, etc.) and models that use more adaptive and sophisticated estimation methods (for example, neural networks and genetic algorithms). An additional way of improving the performance of the overall active investment portfolio of a certain investor may be to hire external managers, whose trading strategies are not correlated nor influenced by the spillover of information and ideas that can happen between in-house managers.

The author has also been using some of the ideas and models described in this thesis in the actual investment process (with varying start dates since January 2003). Up to now, the cumulative performance of the actual model-based investment portfolio on derivatives has been positive and the performance statistics have been comparable to the ones calculated in historical simulations. The author agrees that the existing inefficiencies in the financial markets are under constant pressure by market participants who are trying to exploit them and this can cause the models to lose some of their predictive power in the future. However, considering the relatively large number of different low-correlated strategies presented in this thesis, the chance of all of them losing their predictive power at the same time should be marginal.

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APPENDIXES

Appendix 1. Stationarity tests of the series included in the ARMA models

Logarithm of the EUR/USD exchange rate:
Null Hypothesis: D(LOG_EURUSD) has a unit root. No exogenous variables, lag length 0
Augmented Dickey-Fuller test statistic and probability: –65.35443 (0.0001)
Test critical values: 1% level   –2.565571
                            5% level   –1.940907
                            10% level   –1.616644

Logarithm of the USD/JPY exchange rate:
Null Hypothesis: D(LOG_USDJPY) has a unit root. No exogenous variables, lag length 0
Augmented Dickey-Fuller test statistic and probability: –62.54709 (0.0001)
Test critical values: 1% level   –2.565554
                            5% level   –1.940905
                            10% level   –1.616645

US 10-year government bond future:
Null Hypothesis: D(TY) has a unit root. No exogenous variables, lag length 0
Augmented Dickey-Fuller test statistic and probability: –60.10104 (0.0001)
Test critical values: 1% level   –2.565553
                            5% level   –1.940905
                            10% level   –1.616645

German 10-year government bond future:
Null Hypothesis: D(RX) has a unit root. No exogenous variables, lag length 0
Augmented Dickey-Fuller test statistic and probability: –63.60085 (0.0001)
Test critical values: 1% level   –2.565554
                            5% level   –1.940905
                            10% level   –1.616645

Appendix 2. Selected statistics of the estimated ARMA models and their residuals

The statistics of the estimated equations for the last 259-day period

Estimation Method: Least Squares
Sample: 1/03/2006 12/29/2006
Observations included: 259

Dependent variable: dlog(EUR_USD)

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000866	0.000661	1.310199	0.1913
SEAS(1)	−0.000682	0.000929	−0.733706	0.4638
SEAS(2)	0.000118	0.000935	0.126613	0.8993
SEAS(3)	−0.000788	0.000937	−0.841290	0.4010
SEAS(4)	−0.000860	0.000931	−0.923458	0.3567
AR(1)	−0.469849	0.562330	−0.835540	0.4042
MA(1)	0.490269	0.558173	0.878345	0.3806

R-squared	0.018799	Mean dependent var	0.000426
Adjusted R-squared	−0.004563	S.D. dependent var	0.004735
S.E. of regression	0.004745	Sum squared resid	0.005675
Durbin-Watson stat	2.010665	Prob (F-statistic)	0.567082

Dependent variable: dlog(USD_JPY)

	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.000330	0.000710	−0.465197	0.6422
SEAS(1)	0.001472	0.000979	1.502969	0.1341
SEAS(2)	−0.000455	0.001011	−0.450081	0.6530
SEAS(3)	0.000232	0.001012	0.229289	0.8188
SEAS(4)	0.000610	0.000981	0.622216	0.5344
AR(1)	−0.720059	0.131193	−5.488563	0.0000
MA(1)	0.847804	0.100992	8.394799	0.0000

|			
R-squared	0.052936	Mean dependent var	0.000039
Adjusted R-squared	0.030387	S.D. dependent var	0.004992
S.E. of regression	0.004916	Sum squared resid	0.006090
Durbin-Watson stat	2.042685	Prob (F-statistic)	0.031786

Dependent variable: d(USD_10year_future)

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027590	0.035370	0.780037	0.4361
SEAS(1)	−0.097211	0.048940	−1.986331	0.0481
SEAS(2)	−0.026411	0.050171	−0.526417	0.5991
SEAS(3)	0.004868	0.050180	0.097006	0.9228
SEAS(4)	−0.052238	0.049234	−1.061018	0.2897
AR(1)	−0.254232	1.232464	−0.206279	0.8367
MA(1)	0.297878	1.216316	0.244902	0.8067

R-squared	0.027590	Mean dependent var		−0.006636
Adjusted R-squared	0.001034	S.D. dependent var		0.254418
S.E. of regression	0.254287	Sum squared resid		16.29478
Durbin-Watson stat	2.004357	Prob (F-statistic)		0.396923

Dependent variable: d(Germany_10year_future)

	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.009578	0.038886	−0.246308	0.8056
SEAS(1)	−0.053090	0.054996	−0.965337	0.3353
SEAS(2)	−0.045231	0.054715	−0.826666	0.4092
SEAS(3)	0.102463	0.054724	1.872361	0.0623
SEAS(4)	−0.040154	0.055185	−0.727630	0.4675
AR(1)	−0.070416	1.093511	−0.064395	0.9487
MA(1)	0.063644	1.095794	0.058080	0.9537

|				
R-squared	0.042895	Mean dependent var		−0.016602
Adjusted R-squared	0.020107	S.D. dependent var		0.280600
S.E. of regression	0.277765	Sum squared resid		19.44264
Durbin-Watson stat	1.998960	Prob (F-statistic)		0.084281

The graphs of the models' residuals for the entire test period. The tests for the normal distribution, autocorrelation and stationarity of the models' residuals.

d(log(EUR_USD))_forecast-d(log(EUR_USD))_actual
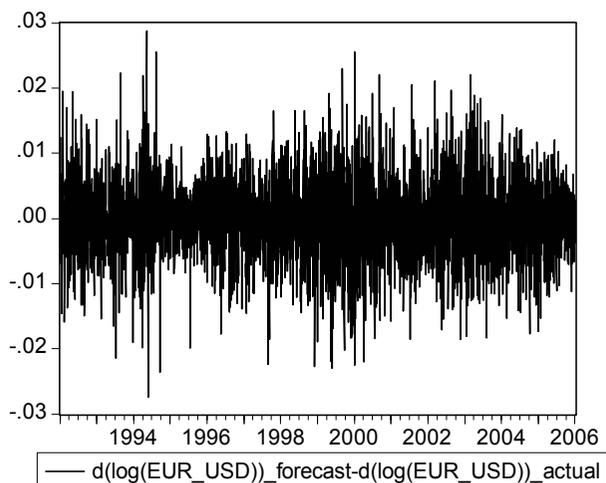
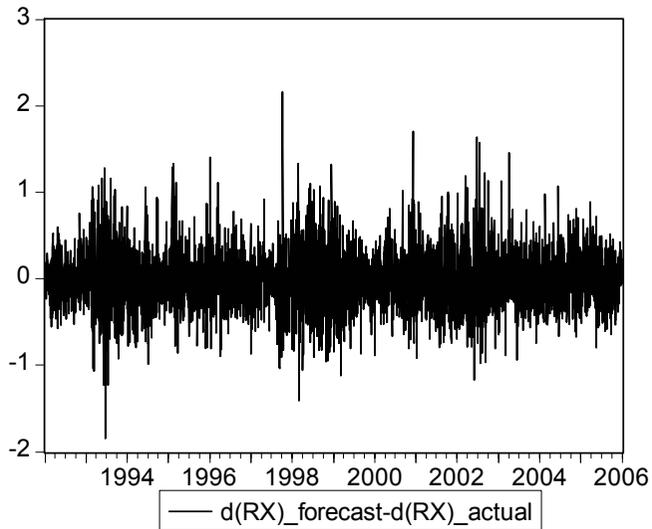P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.901
                                                            lag 2:   0.983
                                                            lag 3:   0.985
ADF test-statistic for stationarity and 1% critical value: −26.63820 (−2.5663)
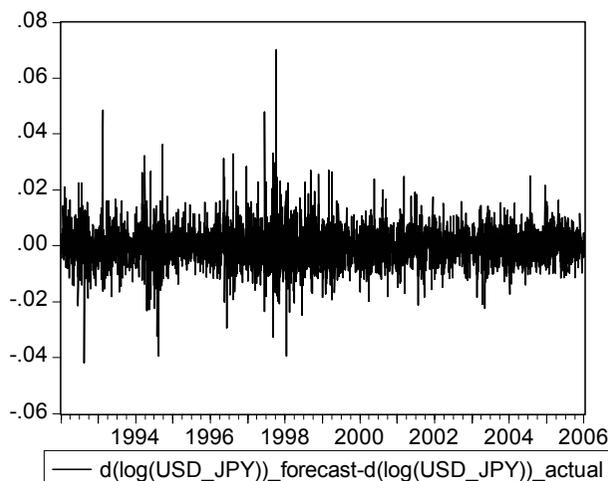
d(log(USD_JPY))_forecast-d(log(USD_JPY))_actual

P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.947
                                                            lag 2:   0.997
                                                            lag 3:   1.000
ADF test-statistic for stationarity and 1% critical value: −27.16280 (−2.5663)
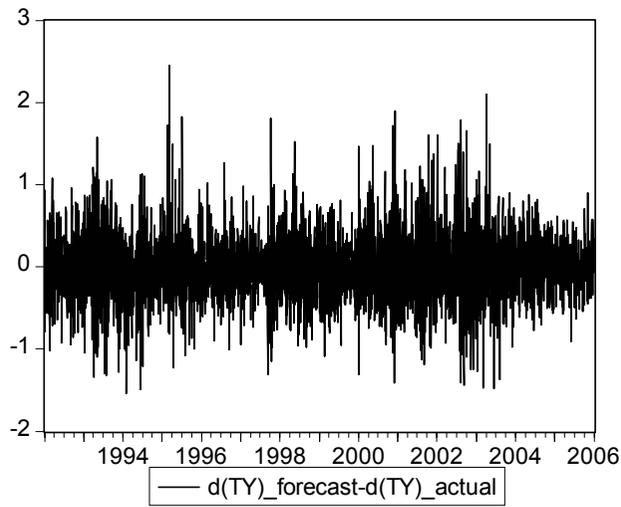
P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.665
                                                           lag 2:   0.881
                                                           lag 3:   0.127
ADF test-statistic for stationarity and 1% critical value: −28.61161 (−2.5663)

P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.718
                                                           lag 2:   0.936
                                                           lag 3:   0.859
ADF test-statistic for stationarity and 1% critical value: −27.33868 (−2.5663)

Appendix 3. Selected statistics of the estimated duration model and its residuals

The statistics of the estimated equations for the last 10-year period

Estimation Method: Least Squares
Sample: 1997M01 2006M12
Observations included: 120
Total system (balanced) observations: 360

	Coefficient	Std. Error	t-Statistic	Prob.
C_1	0.004445	0.050608	0.087823	0.9301
C_2	0.156792	0.052583	2.981819	0.0031
C_3	0.177499	0.052299	3.393912	0.0008
C_4	0.172399	0.053395	3.228721	0.0014
C_5	0.055091	0.051690	1.065804	0.2872
C_6	0.090655	0.054791	1.654571	0.0989
Determinant residual covariance		0.292028		

Equation: $R_{G,n}=c_1+c_2*CR_{G,n,t-1}+c_3*V_{G,n,t-1}+c_4*CY_{G,n,t-1}+c_5*FX_{G,n,t-1}+c_6*R_{G,n,t-1}$

R-squared	0.072543	Mean dependent var	0.006247
Adjusted R-squared	0.031865	S.D. dependent var	1.001819
S.E. of regression	0.985728	Sum squared resid	110.7693
Durbin-Watson stat	1.889077		

Equation: $R_{U,n}=c_1+c_2*CR_{U,n,t-1}+c_3*V_{U,n,t-1}+c_4*CY_{U,n,t-1}+c_5*FX_{U,n,t-1}+c_6*R_{U,n,t-1}$

| R-squared	0.095988	Mean dependent var	0.011423
Adjusted R-squared	0.056339	S.D. dependent var	0.996234
S.E. of regression	0.967764	Sum squared resid	106.7687
Durbin-Watson stat	2.111446		

Equation: $R_{J,n}=c_1+c_2*CR_{J,n,t-1}+c_3*V_{J,n,t-1}+c_4*CY_{J,n,t-1}+c_5*FX_{J,n,t-1}+c_6*R_{J,n,t-1}$

R-squared	0.087042	Mean dependent var	0.007671
Adjusted R-squared	0.047000	S.D. dependent var	1.000611
S.E. of regression	0.976814	Sum squared resid	108.7749
Durbin-Watson stat	1.885272		

The graphs of the models' residuals for the entire test period. The tests for the normal distribution, autocorrelation and stationarity of the models' residuals.

— Residual_Germany
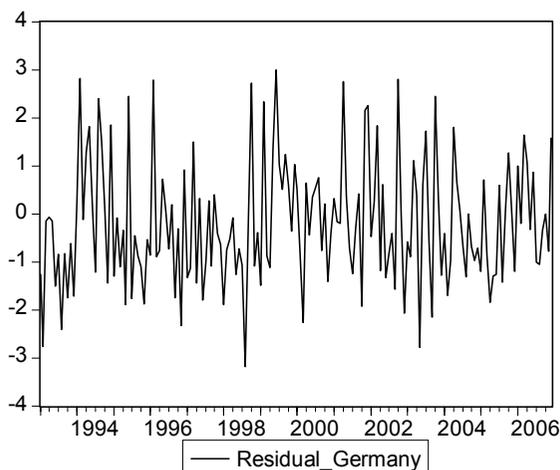
P-value of Jarque-Bera test of normal distribution: 0.023701
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.857
                                                              lag 2:   0.879
                                                              lag 3:   0.498
ADF test-statistic for stationarity and 1% critical value: −4.740487 (−2.5778)

— Residual_USA
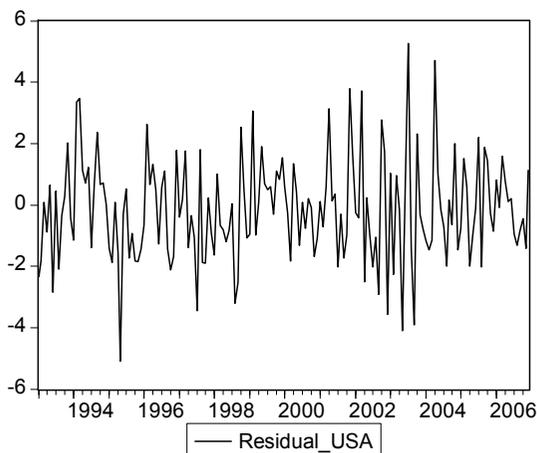
P-value of Jarque-Bera test of normal distribution: 0.065600
P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.907
                                                              lag 2:   0.140
                                                              lag 3:   0.056
ADF test-statistic for stationarity and 1% critical value: −5.271233 (−2.5778)

P-value of Jarque-Bera test of normal distribution: 0.000000

P-value of Ljung-Box Q-statistic for serial correlation,   lag 1:   0.250

lag 2:   0.324

lag 3:   0.018

ADF test-statistic for stationarity and 1% critical value: −6.935921 (−2.5778)

Appendix 4. Selected statistics of the estimated yield curve model on swaps and its residuals

The statistics of the estimated equations for the last 10-year period

Estimation Method: Least Squares
Sample: 1997M01 2006M12
Observations included: 120
Total system (balanced) observations: 240

	Coefficient	Std. Error	t-Statistic	Prob.
C_1	−0.038231	0.088099	−0.433957	0.6647
C_2	−0.013896	0.029019	−0.478839	0.6325
C_3	−0.010893	0.067151	−0.162212	0.8713
C_4	−0.025869	0.065844	−0.392881	0.6948
C_5	−0.047454	0.065866	−0.720473	0.4720
C_6	−0.197115	0.066820	−2.949920	0.0035
C_7	−0.014367	0.066858	−0.214886	0.8300
Determinant residual covariance	0.897386			

Equation (US):

$$S_{U,n} = c_1 + c_2*CR_{U,n,t-1} + c_3*V_{U,n,t-1} + c_4*CY_{U,n,t-1} + c_5*FX_{U,n,t-1} + c_6*R_{U,n,t-1} + c_7*MP_{U,,n,t-1} + c_8*S_{U,n,t-1}$$

R-squared	0.077557	Mean dependent var	−0.006644
Adjusted R-squared	0.028578	S.D. dependent var	1.001508
S.E. of regression	0.987093	Sum squared resid	110.1019
Durbin-Watson stat	1.972652		

Equation (Japan):

$$S_{J,n} = c_1 + c_2*CR_{J,n,t-1} + c_3*V_{J,n,t-1} + c_4*CY_{J,n,t-1} + c_5*FX_{J,n,t-1} + c_6*R_{J,n,t-1} + c_7*MP_{J,,n,t-1} + c_8*S_{J,n,t-1}$$

R-squared	0.000050	Mean dependent var	−0.012171
Adjusted R-squared	−0.053044	S.D. dependent var	0.995152
S.E. of regression	1.021205	Sum squared resid	117.8431
Durbin-Watson stat	1.965893		

The graphs of the models' residuals for the entire test period. The tests for the normal distribution, autocorrelation and stationarity of the models' residuals.
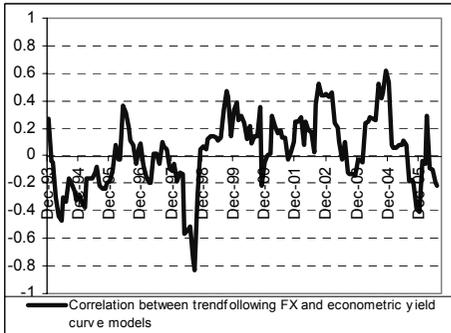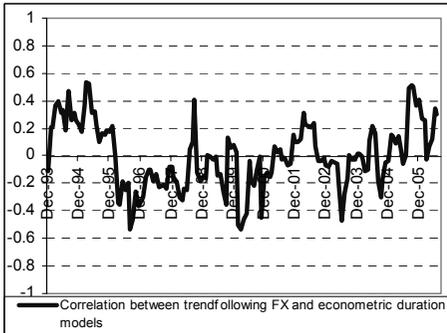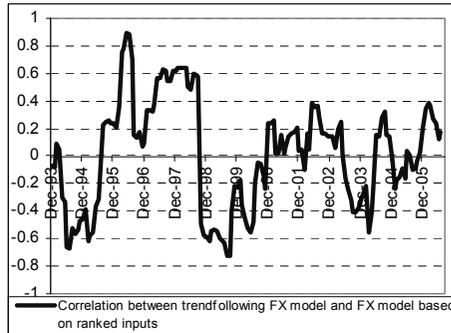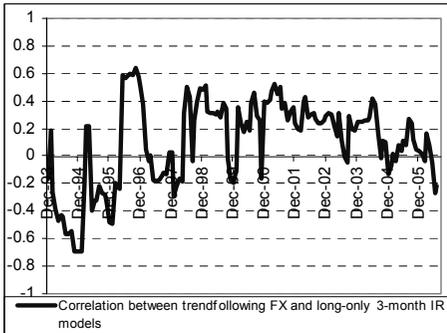

Residual_USA
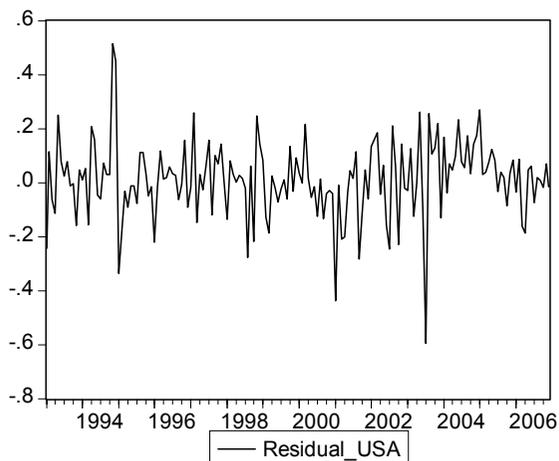
P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation, lag 1: 0.729
                                                          lag 2: 0.445
                                                          lag 3: 0.267
ADF test-statistic for stationarity and 1% critical value: −5.495953 (−2.5782)
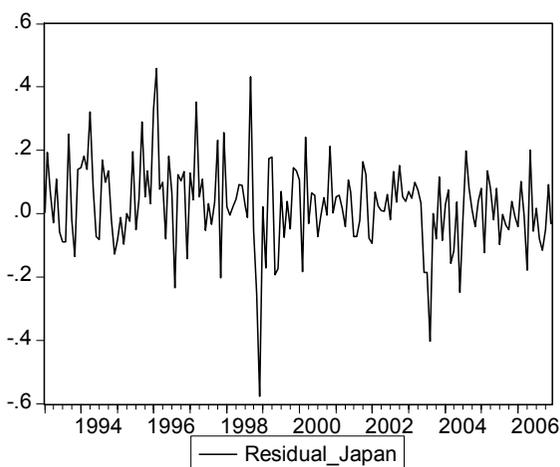
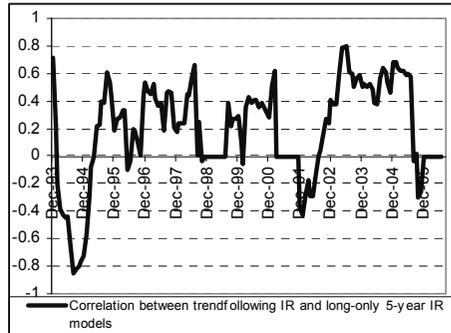Residual_Japan

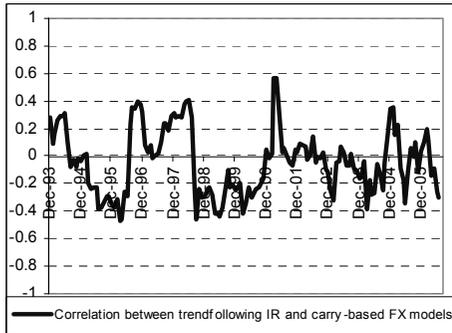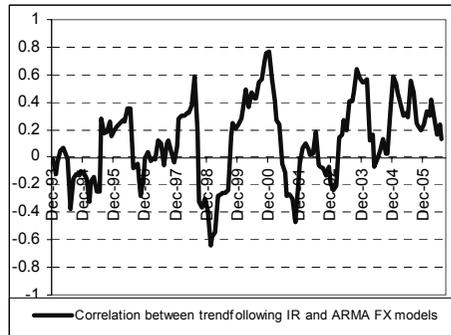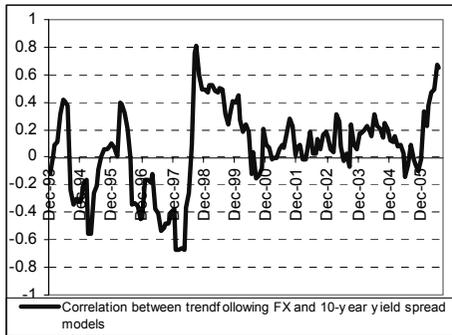P-value of Jarque-Bera test of normal distribution: 0.000000
P-value of Ljung-Box Q-statistic for serial correlation, lag 1: 0.229
                                                          lag 2: 0.356
                                                          lag 3: 0.483
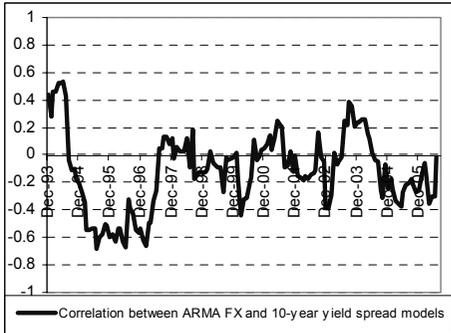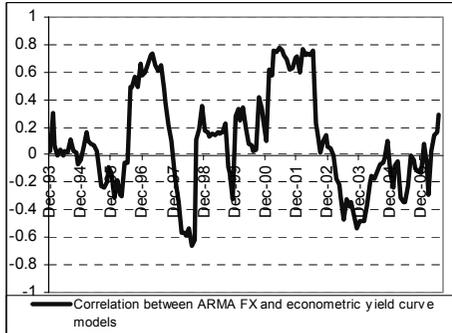ADF test-statistic for stationarity and 1% critical value: −4.844622 (−2.5782)

143

Appendix 5. 12-month rolling correlations of the excess returns from the tested investment models

Correlation between trendfollowing FX and IR models

Correlation between trendfollowing and ARMA FX models

Correlation between trendfollowing and carry-based FX models

Correlation between trendfollowing FX and long-only 5-year IR models

Correlation between trendfollowing FX and long-only 3-month IR models

Correlation between trendfollowing FX model and FX model based on ranked inputs

Correlation between trendfollowing FX and econometric duration models

Correlation between trendfollowing FX and econometric yield curve models

144

Correlation between trendfollowing FX and 10-year yield spread models

Correlation between trendfollowing IR and ARMA FX models

Correlation between trendfollowing IR and carry-based FX models

Correlation between trendfollowing IR and long-only 5-year IR models

Correlation between trendfollowing IR and long-only 3-month IR models

Correlation between trendfollowing IR model and FX model based on ranked inputs

Correlation between trendfollowing IR and econometric duration models

Correlation between trendfollowing IR and econometric yield curve models

145

Correlation between trendfollowing IR and 10-year yield spread models

Correlation between ARMA FX and carry-based FX models

Correlation between ARMA FX and long-only 5-year IR models

Correlation between ARMA FX and long-only 3-month IR models

Correlation between ARMA FX model and FX model based on ranked inputs

Correlation between ARMA FX and econometric duration models

Correlation between ARMA FX and econometric yield curve models

Correlation between ARMA FX and 10-year yield spread models

146

Correlation between carry-based FX and long-only 5-year IR models

Correlation between carry-based FX and long-only 3-month IR models

Correlation between carry-based FX model and FX model based on ranked inputs

Correlation between carry-based FX and econometric duration models

Correlation between carry-based FX and econometric yield curve models

Correlation between carry-based FX and 10-year yield spread models

Correlation between long-only 5-year and long-only 3-month IR models

Correlation between long-only 5-year IR model and FX model based on ranked inputs

Correlation between long-only 5-year IR and econometric duration models

Correlation between long-only 5-year IR and econometric yield curve models

Correlation between long-only 5-year IR and 10-year yield spread models

Correlation between long-only 3-month IR model and FX model based on ranked inputs

Correlation between long-only 3-month IR and econometric duration models

Correlation between long-only 3-month IR and econometric yield curve models

Correlation between long-only 3-month IR and 10-year yield spread models

Correlation between FX model based on ranked inputs and econometric duration model

Correlation between FX model based on ranked inputs and econometric yield curve model

Correlation between FX model based on ranked inputs and 10-year yield spread model

Correlation between econometric duration and yield curve models

Correlation between econometric duration and 10-year yield spread models

Correlation between econometric yield curve and 10-year yield spread models

Appendix 6. Calculating the value of Australian government bond futures from their price

Source: Sydney Futures Exchange
[http://www.sfe.com.au/content/sfe/products/pricing.pdf]

The value of Australian 10-year or 3-year government bond futures can be calculated from their price using the following formulae:

$$V = 1000 * \left[\frac{c(1-v^n)}{i} + 100v^n \right]$$

$$v = v/(1+i)$$

$$i = (100-P)/200$$

where: V - value of futures contract
    c - coupon rate / 2 (6/2=3 for both 10- and 3-year futures)
        n – number of half-years until maturity (20 for 10-year futures and 6 for 3-year futures)
        i – yield per annum divided by 200
        P – price of futures contract.

Appendix 7. Statistical properties of the excess return series from the different models

Statistical properties of the excess returns from the daily foreign exchange model based on two moving averages
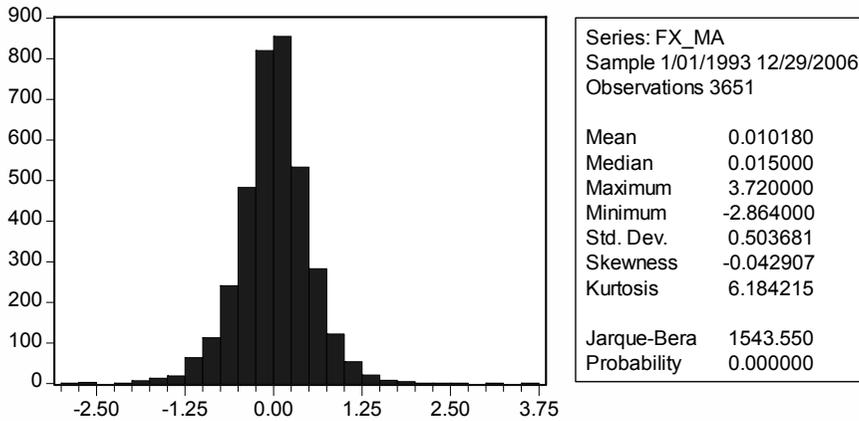
Series: FX_MA	
Sample 1/01/1993 12/29/2006	
Observations 3651	
Mean	0.010180
Median	0.015000
Maximum	3.720000
Minimum	-2.864000
Std. Dev.	0.503681
Skewness	-0.042907
Kurtosis	6.184215
Jarque-Bera	1543.550
Probability	0.000000

Statistical properties of the excess returns from the daily interest rate model based on two moving averages

Series: IR_MA	
Sample 1/01/1993 12/29/2006	
Observations 3651	
Mean	9.046836
Median	13.00000
Maximum	1870.000
Minimum	-1682.000
Std. Dev.	293.5858
Skewness	-0.093736
Kurtosis	5.735236
Jarque-Bera	1143.472
Probability	0.000000
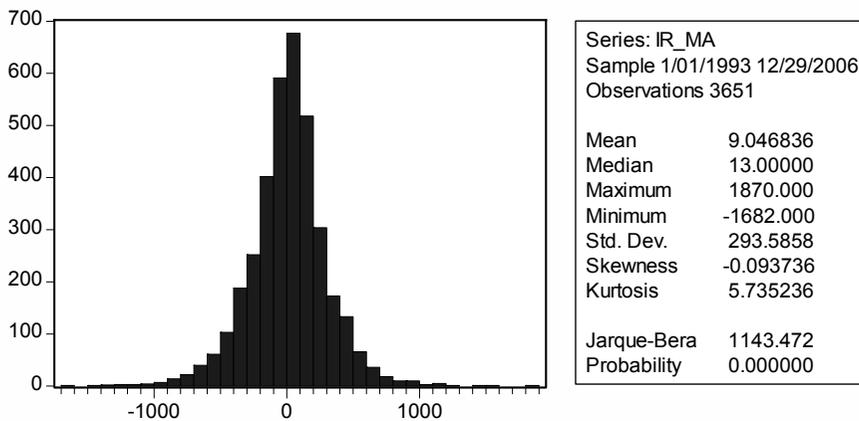
Statistical properties of the excess returns from the daily foreign exchange model based on ARMA methodology
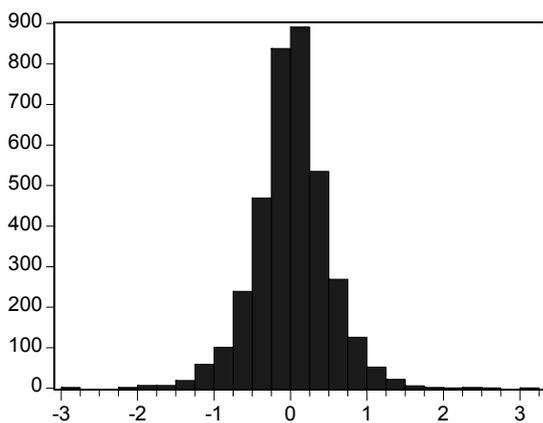
Series: FX_ARMA	
Sample 1/01/1993 12/29/2006	
Observations 3651	
Mean	0.016936
Median	0.025000
Maximum	3.189000
Minimum	-2.989000
Std. Dev.	0.486974
Skewness	-0.102942
Kurtosis	5.711053
Jarque-Bera	1124.538
Probability	0.000000

Statistical properties of the excess returns from the daily interest rate model based on ARMA methodology
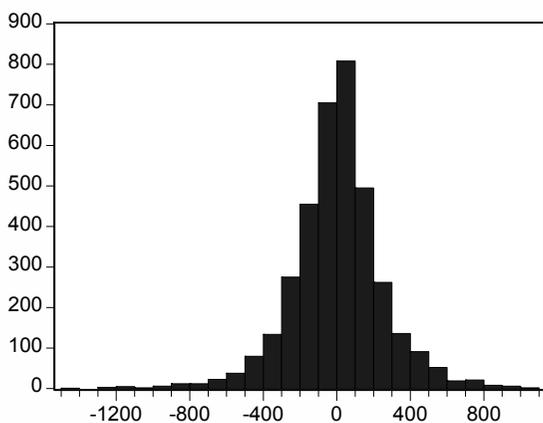
Series: IR_ARMA	
Sample 1/01/1993 12/29/2006	
Observations 3651	
Mean	1.155300
Median	4.000000
Maximum	1032.000
Minimum	-1401.000
Std. Dev.	250.5099
Skewness	-0.255019
Kurtosis	5.868559
Jarque-Bera	1291.354
Probability	0.000000

Statistical properties of the excess returns from the monthly foreign exchange model based on risk-adjusted carry

Series: FX_CARRY	
Sample 1993M01 2006M12	
Observations 168	
Mean	0.673036
Median	0.680000
Maximum	4.090000
Minimum	-3.910000
Std. Dev.	1.498733
Skewness	-0.423620
Kurtosis	3.684107
Jarque-Bera	8.300718
Probability	0.015759
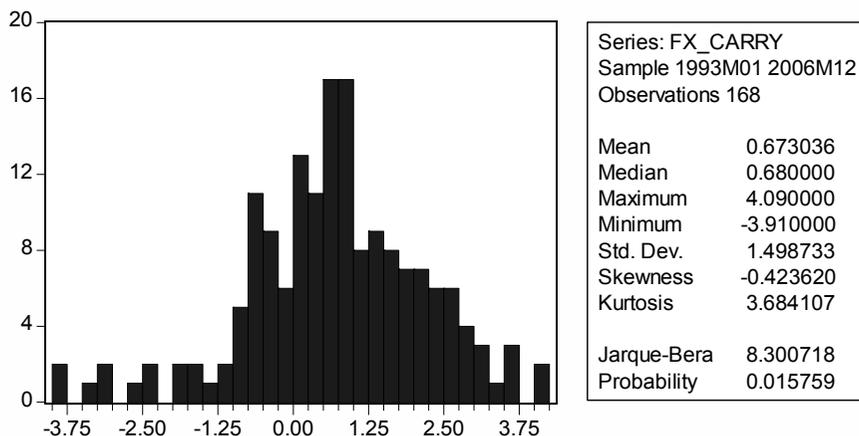
Statistical properties of the excess returns from the interest rate model based on the structural time premium and implemented with 5-year government bond futures
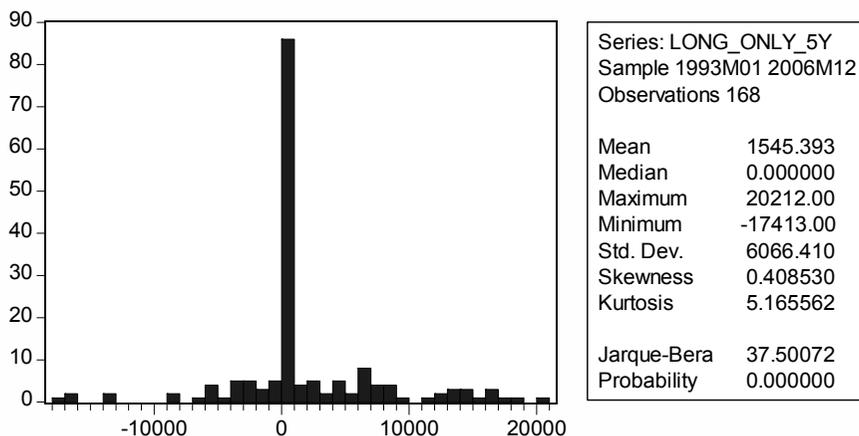
Series: LONG_ONLY_5Y	
Sample 1993M01 2006M12	
Observations 168	
Mean	1545.393
Median	0.000000
Maximum	20212.00
Minimum	-17413.00
Std. Dev.	6066.410
Skewness	0.408530
Kurtosis	5.165562
Jarque-Bera	37.50072
Probability	0.000000

Statistical properties of the excess returns from the interest rate model based on the structural time premium and implemented with 3-month interest rate futures
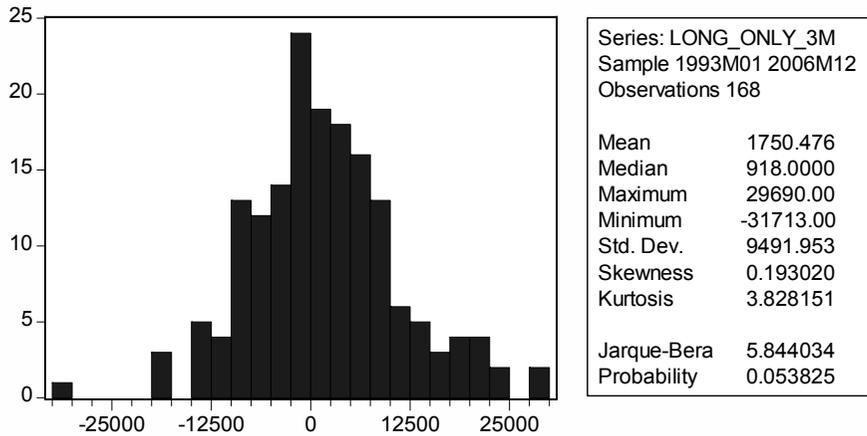
Series: LONG_ONLY_3M	
Sample 1993M01 2006M12	
Observations 168	
Mean	1750.476
Median	918.0000
Maximum	29690.00
Minimum	-31713.00
Std. Dev.	9491.953
Skewness	0.193020
Kurtosis	3.828151
Jarque-Bera	5.844034
Probability	0.053825

Statistical properties of the excess returns from the monthly foreign exchange model based on four ranked inputs

Series: FX_RANKED_INPUTS	
Sample 1993M01 2006M12	
Observations 168	
Mean	0.652083
Median	0.715000
Maximum	7.140000
Minimum	-6.110000
Std. Dev.	1.929537
Skewness	-0.175658
Kurtosis	4.035039
Jarque-Bera	8.363103
Probability	0.015275

154
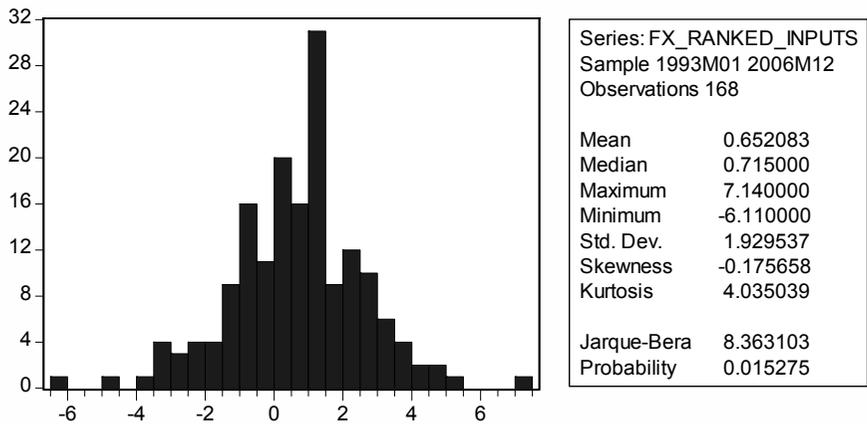
Statistical properties of the excess returns from the monthly duration model

Series: DURATION	
Sample 1993M01 2006M12	
Observations 168	
Mean	11337.74
Median	10868.50
Maximum	87242.00
Minimum	-60220.00
Std. Dev.	29013.69
Skewness	0.166984
Kurtosis	3.220574
Jarque-Bera	1.121315
Probability	0.570834
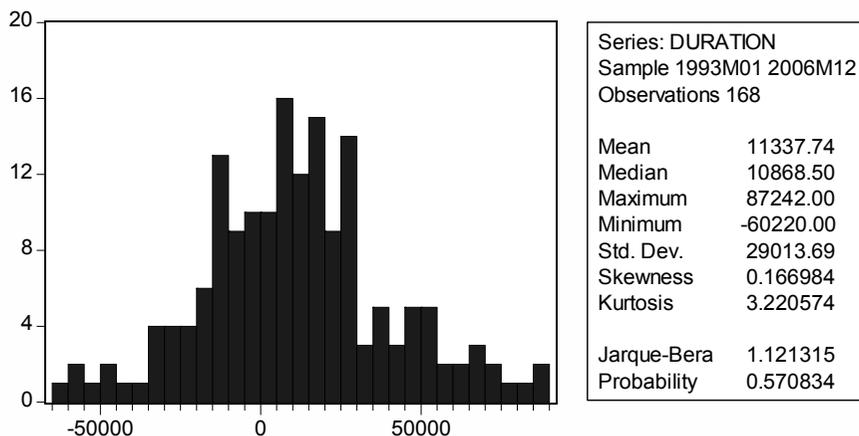
Statistical properties of the excess returns from the monthly yield curve model

Series: YIELD_CURVE	
Sample 1993M01 2006M12	
Observations 168	
Mean	0.017738
Median	0.020000
Maximum	0.310000
Minimum	-0.320000
Std. Dev.	0.096779
Skewness	-0.390197
Kurtosis	4.482153
Jarque-Bera	19.64056
Probability	0.000054
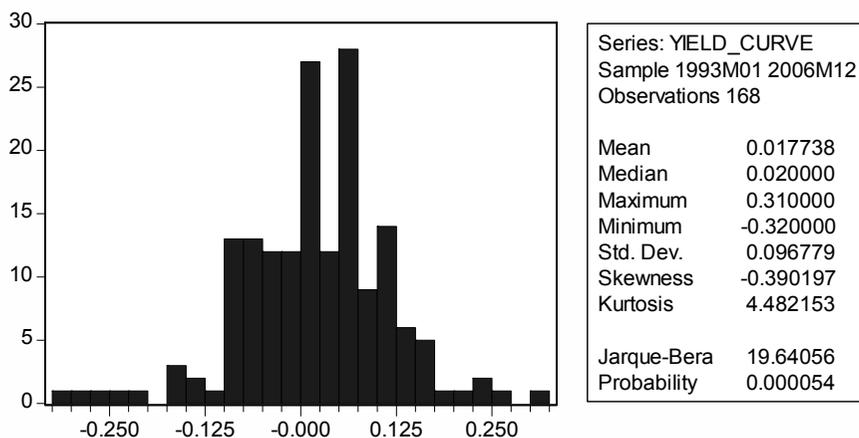
Statistical properties of the excess returns from the monthly cross-country yield spread model

Series: CROS_COUNTRY_IR	
Sample 1993M01 2006M12	
Observations 168	
Mean	0.356667
Median	0.385000
Maximum	4.690000
Minimum	-4.860000
Std. Dev.	1.171241
Skewness	-0.239804
Kurtosis	7.120550
Jarque-Bera	120.4627
Probability	0.000000
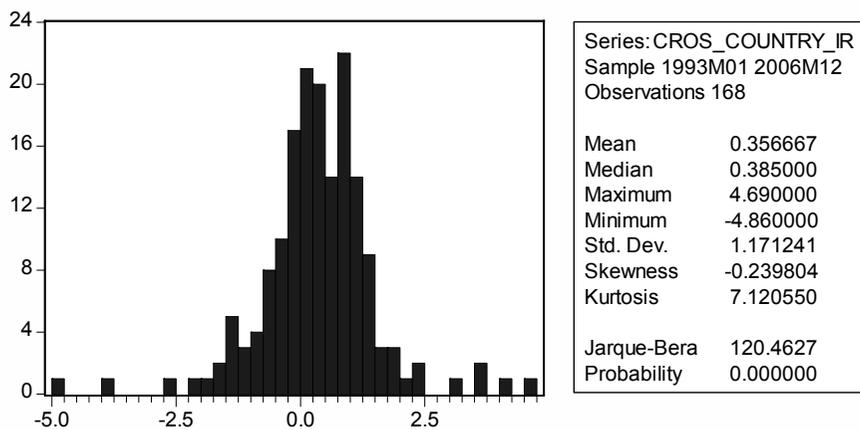
SUMMARY IN ESTONIAN – KOKKUVÕTE

METOODIKA HAJUTATUD KVANTITATIIVSETE AKTIIVSE INVESTEERIMISE MUDELITE PORTFELLI ABIL GLOBAALSETEL VÕLAKIRJA- JA VALUUTATURGUDEL LISATULU TEENIMISEKS

Töö aktuaalsus

Viimastel aastatel rahvusvahelistel võlakirjaturgudel valitsenud madalad intressimäärad ning 2000.–2001. aastal järsu languse läbi teinud aktsiaturud on tuntavalt vähendanud passiivse investeerimisstiili[75] tulusust arenenud riikide finantsturgudel. Vähenenud tulusus ning oht, et intressimäärade kiire tõusuga kaasnev võlakirjahindade langus võib võlakirjainvesteeringute tulusust lähiajal veelgi väheneda, on kaasa toonud aktiivsed otsingud tulususe suurendamise võimaluste leidmiseks. Üheks selliseks võimaluseks on aktiivsed investeerimisotsused, ehk siis otsused hälbida etteantud passiivsest investeerimisportfellist.

Aktiivsed investeerimisotsused võimaldavad investeerimisportfelli kogutulusust suurendada, kui investor suudab turuliikumiste suunda keskmiselt õigesti ennustada või kui leidub varaklasse, mille tulususe ja riski suhe on pikka aega turu keskmisest erinev. Seega eeldavad aktiivsed investeerimisotsused vähemalt minimaalsete ebaefektiivsuste eksisteerimist turgudel, millelt on ratsionaalselt efektiivsete turgude hüpoteesi kohaselt (Grossman ja Stiglitz 1980) võimalik ebaefektiivsuste otsimistele aja- ja muid ressursse kulutavatel investoritel teenida lisatulu.

Kasutades erisuguseid tuletisinstrumente, saab ka minimaalsetelt ebaefektiivsustelt piisava võimenduse korral teenida suhteliselt suuri lisakasumeid/ kahjumeid. Siit tulenebki doktoritöö aktuaalsus – tuletisinstrumentidel rakendatav kasumlik aktiivse investeerimise strateegia võimaldaks investoritel tõsta märgatavalt oma investeerimistulusust võrreldes passiivse strateegiaga.

Aktiivse investeerimise populaarsuse kiiret kasvu näitab ilmekalt erinevate riskifondide (*hedge funds*) poolt hallatavate varade mahu kiire kasv: maailmas riskifondide poolt hallatavad varad on 1990. aastast 2006. aastani kasvanud ligi 35 korda, jõudes umbes 1.4 triljoni dollari tasemeni (Loeys ja Fransolet 2004, lk

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[75] Turuindeksit järgiv investeerimisstiil, mis ei ürita saavutada turuindeksist paremat tulusust (www.investopedia.com).

3 ja *Hedge Fund Research, Inc* veebileht). Samuti on erinevate aktiivse inves-
teerimise võimaluste otsimisele kaasa aidanud arvutite kiire levik, mis võimal-
dab kiiresti töödelda suuri andmemasse ja varasemate andmete põhjal testida
erinevaid kauplemisstrateegiaid. Aktiivse investeerimisega lisatulu teenida
üritavate investorite arvu järsk suurenemine on oluliselt vähendanud aktiivse
tulususe võimalikkust aktsiaturgudel. Nii näiteks ei suutnud 31.07.2005. a seisu-
ga CISDMi (*Centre for International Securities and Derivatives Markets*) and-
metel viimase 10 aasta jooksul enamik riskifondidest, investeerimisnõustajatest
ning futuurifondidest ületada S&P500 aktsiaindeksi tootlust[76]. Samuti võib
leida mitmeid artikleid (nt Fong ja Young.2005 jt), kus näidatakse mingi kindla
kauplemisstrateegia suutmatust teenida aktsiaturgudel aktiivselt stabiilset posi-
tiivset lisatulu.

Aktiivse investeerimise tulemuslikkus turgudel sõltub tulusaamise ning
muude eesmärkidega turuosaliste suhetest turul. Aktsiaturule oma varasid paigu-
tavate investorite põhieesmärgiks on üldjuhul riskiga kaalutud tulususe maksi-
meerimine, mistõttu aktsiaturgude efektiivsus on erinevate varaklasside turgu-
dest suurim ning aktiivsete investeerimisotsustega lisatulu teenimise võimalused
väikseimad. Teistsugune on olukord valuuta- ja võlakirjaturgudel, kus suhteli-
selt suur osa tehingutest toimub ilma spekulatiivse kasu saamise eesmärgita[77].
Seetõttu keskendutakse doktoritöös aktiivse investeerimise strateegia välja-
töötamisel just arenenud riikide võlakirja- ja valuutaturgudele ning ega käsitleta
aktsiaturge.

Aktiivse investeerimise otsuseid saab vastu võtta subjektiivselt erisuguseid
turgude mõjutegureid hinnates või reeglipäraselt eelnevalt testitud seoste abil
saadud investeerimissignaalidele tuginedes. Doktoritöös käsitletakse ainult
reeglipäraseid, varasemal kvantitatiivsel analüüsil baseeruvaid otsuseid, sest
sellisest analüüsist tulenevad otsused on ajas konsistentsed ning nende võima-
likku tulusust ja riski kajastavad statistikud on ajaloolise testperioodi põhjal
üheselt väljaarvutatavad.

Vastavalt aktiivse investeerimise seadusele (Clarke jt 2002, lk 50) on aktiiv-
selt hallatava investeerimisportfelli tulususe ja riski suhe positiivses sõltuvuses
iga üksiku investeerimisstrateegia oodatava tulususe ja riski suhtest ning
vähekorreleeritud erinevate aktiivse investeerimise strateegiate arvust. Seega,
kogu portfelli tulususe ja riski suhte parandamiseks tuleks parandada kas erine-
vate üksikute investeerimisstrateegiate tulususe ja riski suhet või suurendada
vähekorreleeritud investeerimisstrateegiate arvu. Esimene võimalus on finants-

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[76] Antud andmestik on arvutatud samas väga väikese valimi põhjal (kokku 30 fondi).

[77] Nt keskpankade rahaturuoperatsioonid baasintressi taseme muutmiseks lähtuvad
poliitilistest eesmärkidest (põhiliselt inflatsiooni eesmärgistamine või majanduskasvu
stabiliseerimine) ning väliskaubandusega tegelevate ettevõtete valuutatehingud vajadu-
sest maandada kas tootmissisendite või toodangu müügi hinnariske (Collins jt 2005, lk
76).

turgude suhteliselt kõrge efektiivsuse tõttu raskelt saavutatav, mistõttu doktoritöös pööratakse põhjalikult ja süstemaatiliselt tähelepanu teisele võimalusele.

Kuigi erisuguste üksikute investeerimismudelite kombineerimisest tulenevat kogu portfelli tulususe ja riski suhte paranemist on ka varem uuritud (nt Ilmanen ja Sayood 2002), on senised uuringud piirdunud vaid mõne mudeliga. Doktoritöö astub siinkohal sammu edasi ning laiendab hajutatud mudelite portfelli, koostades tervikliku komplekti erineval arvul (ühe- ja mitmetegurilised mudelid) erisuguseid sisendeid (nii fundamentaalmajanduslikud sisendid kui ka finantsinstrumentide enda hinna-aegread) kasutavatest eri tüüpi (ökonomeetrilised regressioonmudelid, järjestusmudelid ning tehnilised mudelid) investeerimismudelitest.

Töö eesmärk ja ülesanded

Doktoritöö eesmärgiks on välja töötada metoodika, kuidas aktiivsete investeerimisotsustega teenida lisatulu arenenud riikide võlakirja- ja valuutaturgudel. Selleks kasutatakse hajutatud kvantitatiivsete investeerimismudelite portfelli. Antud metoodikat oleks võimalik rakendada investeerimistulemuste parandamiseks kõigil antud turgudel investeerivatel investoritel, sealhulgas keskpankadel, kindlustusseltsidel, pensionifondidel ning mitmesugustel riskifondidel.

Doktoritöö eesmärgi saavutamiseks lahendatakse töös alljärgnevad uurimisülesanded.

1. Uurida avaldatud kirjanduse põhjal, millistel tingimustel ja turgudel on suuremad võimalused teenida aktiivse investeerimisega positiivset lisatulu.
2. Uurida lähemalt erisuguseid investeerimisstiile, investeerimismudelite ülesehitusvõimalusi ning võimalikke sisendtegureid, eesmärgiks koostada empiiriliselt hinnatava mudelportfelli teoreetiline struktuur.
3. Hinnata empiiriliselt erisuguseid kvantitatiivseid investeerimismudeleid ning testida ajalooliste andmete põhjal nende tulemuslikkust.
4. Uurides ja testides mitmesuguseid mudelite kombineerimise võimalusi, leida optimaalseim viis, kuidas väljatöötatud mudelitest koostada ühtne portfell.
5. Teha järeldused väljatöötatud kvantitatiivsete investeerimismudelite portfelli rakendamisel saavutatava võimaliku lisatulususe ja riskiastme kohta ning erinevate mudelite kombineerimisega saavutatava lisatulususe – riski suhte paranemise kohta, võrreldes üksikute investeerimismudelitega.

Töö struktuur

Doktoritöö koosneb kahest osast. Esimeses osas töötatakse eelnevalt avaldatud kirjanduse baasil välja teoreetiline metodoloogia, kuidas kvantitatiivsete aktiivse investeerimise mudelite portfelli abil teenida rahvusvahelistel võlakirja- ja valuutaturgudel lisatulu. Töö teises osas hinnatakse väljatöötatud mudelite struktuurile vastavad mudelid empiiriliselt ning tehakse mitmesuguste väljaarvutatud tulusust ja riski kajastavate statistikute alusel järeldused nende kasutusotstarbekuse kohta. Töö lõpeb väljatöötatud mudelite kombineerimisega üheks hajutatud investeerimisportfelliks ning kombineerimisega saavutatava tulususe ja riski suhte paranemise analüüsiga.

Doktoritöö struktuur on kokkuvõtlikult esitatud joonisel 1.
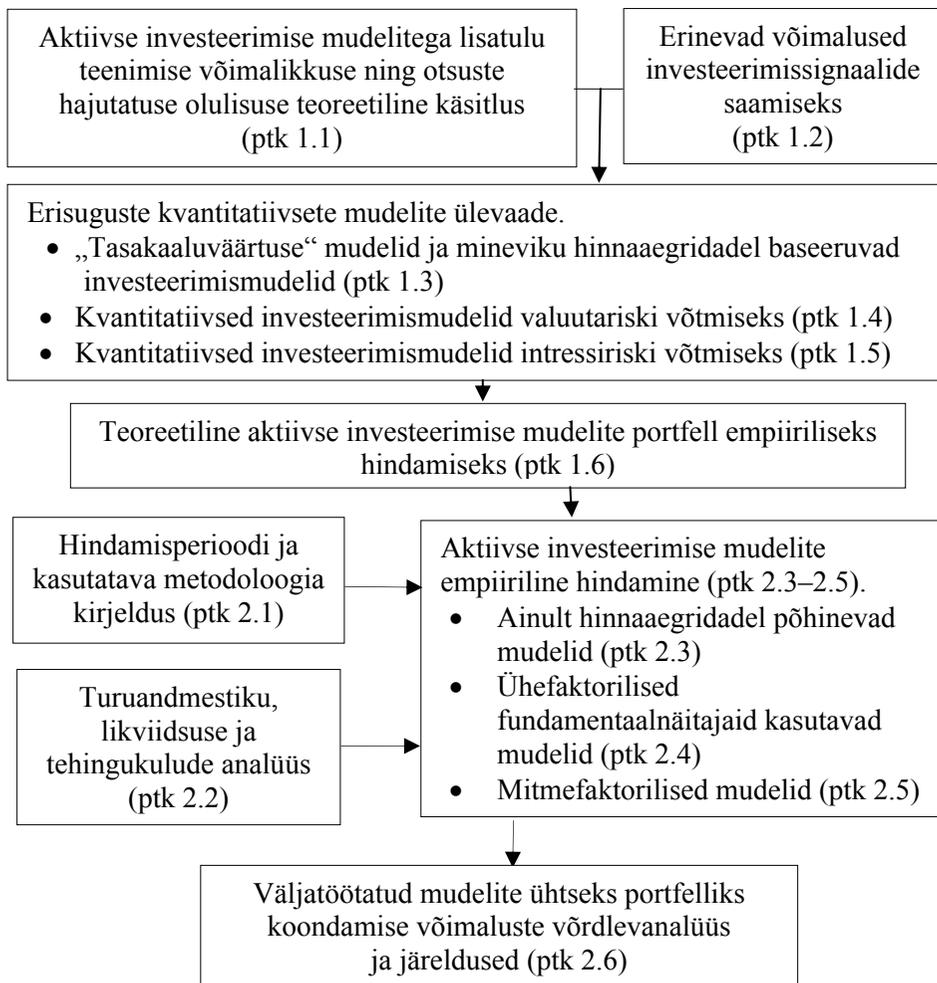
Joonis 1. Doktoritöö struktuuri üldine loogika

Doktoritöö teoreetilise osa esimene alapeatükk (ptk 1.1.1) analüüsib aktiivse investeerimisega lisatulu teenimise võimalikkust erinevatel turgudel. Läbitöötatud kirjanduse baasil jõutakse töös alljärgnevatele järeldusele.

- Ratsionaalselt efektiivsete turgude hüpoteesi kohaselt (Grossman ja Stiglitz 1980) on finantsturgudel suure tõenäosusega, aga ulatuselt väga väikseid ebaefektiivsusi.
- Võrreldes aktsiaturgudega, on suhteliselt suuremad aktiivsete investeerimisotsustega lisatulu teenimise võimalused võlakirja- ja valuutaturgudel, sest neil turgudel on suurem osakaal mittespekulatiivsetel (st mitte turuliikumistelt kasusaamise eesmärgist ajendatud) rahavoogudel, nagu keskpankade majanduspoliitilised otsused muuta baasintressi taset ning väliskaubandusega tegelevate ettevõtete soovid maandada tootmissisendite või müüdava lõpptoodangu valuutakursimuutustest tulenevaid hinnariske.

Alapeatükk 1.1.2 käsitleb otsuste hajutatuse kasulikkust lähtuvalt aktiivse investeerimise seadusest (Clarke jt 2002, lk 50). Finantsturgude kõrge efektiivsuse tõttu ei ole võimalik ühegi üksiku investeerimisstrateegiaga saavutada piisavalt stabiilset lisatulu, kuid kombineerides mitmeid vähekorreleeritud otsuseid, on ka väikese prognoosijõuga investeerimismudeleid kasutades võimalik tulemuste stabiilsust oluliselt suurendada. Näiteks kui üksik investeerimisotsus võib efektiivsete turgude tingimuses olla kasumlik vaid 55%l juhtudest, siis 180st nullkorrelatsiooniga analoogilisest otsusest koosneva portfelli positiivse lisatulu teenimise tõenäosus on juba 95%.

Alapeatükk 1.2 süstematiseerib võimalikud aktiivse investeerimise stiilid ja sisendid ning analüüsib nende tugevusi ja nõrkusi. Seejärel analüüsitakse varemavaldatud kirjanduse põhjal väljatöötatud mudeleid, eesmärgiks välja sõeluda optimaalne hajutatud mudelite komplekt empiiriliseks analüüsiks. Põhjalikumalt käsitletakse ökonomeetrilisi nn tasakaaluväärtuse mudeleid (alapeatükk 1.3.1), hinnaaegridadel baseeruvaid mudeleid (alapeatükk 1.3.2) ning mitmesuguseid majandustegureid sisenditena kasutavaid ühe- ja mitmetegurilisi valuuta- ja intressituru mudeleid (alapeatükid 1.4 ja 1.5). Alapeatükk 1.6 analüüsib varem avaldatud uurimusi erinevate mudelite signaalide kombineerimisvõimalustest, koondab eelneva teoreetilise analüüsi ning fikseerib aktiivse investeerimise mudelite portfelli empiiriliseks hindamiseks.

Empiirilise osa esimene alapeatükk (2.1) fikseerib empiirilisel hindamisel kasutatava ajaperioodi, andmestiku ning väljaarvutatavad mudelite tulusust ja riski kajastavad statistikud. Alapeatükk 2.2 analüüsib kasutatavat andmestikku sügavamalt ning hindab kaubeldavate instrumentide likviidsust ja tehingukulusid. Alapeatükis 2.3 hinnatakse kaks komplekti ainult finantsinstrumentide hinnaaegridasid kasutavaid mudeleid: ARMA mudelite komplekt ja kahe libiseva keskmise lõikumisel baseeruvale tehnilisele analüüsile tuginev mudelite komplekt. Järgnevalt (alapeatükis 2.4) hinnatakse ühefaktorilisi investeerimismudeleid, milleks valuutaturgude jaoks sai teoreetilise osa alusel välja valitud riskiga kaalutud lühiajalise intressimäära vahet kasutav mudel ning võlakirja-

turgude jaoks struktuurset ajapreemiat kasutav mudel. Mitmefaktorilistest mudelitest hinnatakse alapeatükis 2.5 esmalt (2.5.1) 10valuutalisest komplektist nelja sisendteguri suhtelise järjekorra alusel iga kuu kolm aktiivset valuutapositsiooni võttev valuutamudel. Seejärel hinnatakse regressioonanalüüsil baseeruv intressimäära kestvusmudel (alapeatükis 2.5.2) ning intressikõvera lamenemis- ja järsenemisvaateid võttev mudel (alapeatükis 2.5.3). Alapeatükis 2.5.4 hinnatakse valuutamudeliga analoogiliselt sisendtegurite suhtelisel järjekorral baseeruv erinevate riikide 10aastase intressimäära suhteliselt liikumiselt teeniv maamudel.

Empiiriline osa lõpeb alapeatükis 2.6 väljatöötatud mudelite ühtseks portfelliks kombineerimise ja kombineeritud portfellide tulususe ja riski hindamisega. Alapeatükk algab erinevate koondportfelli koostamise võimaluste võrdleva analüüsiga (2.6.1). Edasi kombineeritakse üksikud investeerimismudelid ühtsesse portfelli kolme meetodi: konventsionaalse portfelliteooria (alapeatükk 2.6.2), leptokurtilise portfelliteooria (Kitt 2005) (alapeatükk 2.6.3) ning kaubeldavate instrumentide arvu (alapeatükk 2.6.4) alusel. Alapeatükis 2.6.5 võrreldakse erinevate mudelite kombineerimise meetodite tulemusi ning esitletakse lõplik diversifitseeritud kvantitatiivsete aktiivse investeerimise mudelite portfelli.

Kasutatud andmed ja metoodika

Töös kasutatavad majandusandmete ning finantsinstrumentide aegread pärinevad kolmest allikast: uudiste- ja andmeplatvormilt *Bloomberg*, majandusnäitajate andmebaasist *Reuters EcoWin* ning G-7 majandusprognoose koondavast ajakirjast *Consensus Forecasts*. Finantsinstrumentide likviidsuse andmestik pärineb *Bloomberg*ist. Tehingukulude arvutamisel on lähtutud elektroonilistes kauplemissüsteemides institutsionaalsetele investoritele pakutavatest *bid-ask*-hinnavahedest: valuutaturul on kasutatud *Citibank*i platvormi *FX Trader*, *Dresdner Bank*i platvormi *Click and Trad*e ja UBSi platvormi *FX Trader* ning intressifutuuride tehingukulude arvutamiseks ABN-AMRO panga platvormi *NetOMS* ja *Barclays Capital*i platvormi *BARX Futures*.

Empiirilise osa mudelid on hinnatud erinevat metoodikat kasutades. Libisevatel keskmistel baseeruva tehnilise mudeli hindamisel kasutati optimeerimist programmis MS Excel. Ökonomeetrilised hinnaandmestikul baseeruvad mudelid on hinnatud ARMA mudelina, kasutades statistikapaketti EViews 5.

Ühefaktorilised optimeerimist mittesisaldavad valuuta- ja intressimudelid (riskiga kaalutud lühiajalise intressimäära vahet sisendina kasutav valuutamudel ning ainult pikaajalisi ostupositsioone võttev intressifutuuride mudel) on testitud MS Excelis. Samuti on MS Excelis testitud sisendtegurite suhtelisel järjestusel baseeruvad mitmetegurilised maa- ja valuutamudelid. Intressimäära kestvusmudel ning intressikõvera lamenemis- ja järsenemispositsioonide

signaale andvad mudelid on regressioonmudelid ning need on samuti hinnatud statistikapaketi EViews 5 abil.

Kõik mudelid on testitud tuletisinstrumentidel. Selline lähenemine võimaldab mudelite tulemusi võrrelda nulltulemuse vastu ning võimaldab mudelitest lähtuvat riski kaaluda vastavalt iga investori riski ja tulususe eesmärkidele. Samuti on tuletisinstrumentide abil mugav eraldada erinevaid üksikuid riskikomponente: valuutarisk, intressimäära kestvusrisk, intressikõvera kuju risk ning maadevahelise suhtelise intressimäära muutumise risk.

Empiirilise analüüsi tulemused ja järeldused

Empiirilisel analüüsil testitud erinevatest lähenemisviisidest näitasid nõrgimat tulemust ainult hinnaaegridadel baseeruvad mudelid: libisevaid keskmisi kasutav mudel ning ARMA mudelid. Libisevaid keskmisi kasutava mudeli annualiseeritud *Sharpe* suhe oli valuutaportfellil 0,33 ja intressiportfellil 0,50 ning ARMA metodoloogiat kasutava mudeli annualiseeritud *Sharpe* suhe valuutaportfellil 0,56 ning intressiportfellil 0,07.

Väga headeks tuleb pidada lihtsamate ühefaktoriliste mudelite – riskiga kaalutud lühiajalise intressimäära vahet sisendina kasutava valuutamudeli ning ainult pikaajalisi ostupositsioone võtva intressifutuuri mudeli testitulemusi. Kuigi nende mudelite ülesehitus oli väga lihtne, sisendite arv minimaalne ning teoreetiline tagapõhi pikka aega ja laialdaselt kirjanduses kajastatud, olid testitulemused mitmefaktoriliste mudelitega võrreldavad. Riskiga kaalutud lühiajalise intressimäära vahe alusel igas kuus nelja valuutapositsiooni kaupleva valuutamudeli annualiseeritud *Sharpe* suhe oli testperioodil 1,56, kahes viieaastases futuuris järsu intressikõvera korral ostupositsioone võtva mudeli annualiseeritud *Sharpe* suhe 0,88 ning viie riigi kolmandas[78] kolmekuuse intressimäära futuuris pikaajalisi ostupositsioone võtva mudeli annualiseeritud *Sharpe* suhe 0,64.

Erisuguste sisendtegurite suhtelisel järjekorral baseeruvate valuuta- ja maamudelite testitulemused olid samuti igati head, eriti arvestades minimaalset optimeerimist antud mudelite testimisel. Kümnest valuutast iga kuu kolme valuutapaari kaupleva valuutamudeli annualiseeritud *Sharpe* suhe testperioodil oli 1,17 ning iga kuu seitsmest riigist kahe riikide paari 10aastaste valitsus-võlakirjade intressivahet kaupleva mudeli annualiseeritud *Sharpe* suhe test-perioodil oli 1,05.

Ökonomeetrilisel regressioonanalüüsil baseeruv intressimäära kestvusmudel oli eelnevate mudelitega võrreldavate heade testitulemustega, kuid antud mudeli juures tuleb arvestada suhteliselt suuremat optimeerimise astet, mis võib kaasa

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[78] Kolmas futuur on futuur, mille lõpptähtaeg on kauplemispäevast arvates kolmandal kvartali viimasel kuul, st näiteks veebruari kuus kaubeldes on kolmandaks futuuriks sama aasta septembrikuu lõpptähtajaga futuur.

tuua tulususe vähenemise tulevikus. Samas peaks tulususe võimalik halvene-mine olema siiski minimaalne, sest ka testperioodil mudeli poolt väljastatud investeerimissignaalid olid rangelt väljaspool võrrandite hindamisel kasutatud ajaperioodi, samuti järgiti rangelt andmestiku kättesaadavuse viitaegu. Intressi-määra kestvusmudel saavutas kolme riigi (USA, Saksamaa ja Jaapani) 10aastas-te valitsusvõlakirjade futuuridega kaubeldes annualiseeritud *Sharpe*'i suhteks 1,35. Analoogiliselt testitud intressimäära kõvera kuju mudel saavutas USA ja Jaapani turul kaubeldes annualiseeritud *Sharpe*'i suhteks 0,64.

Testitud mudelite kuise ja päevase lisatulu statistilise jaotuse analüüs näitas meile, et mudelite tulususid on enamasti leptokurtilise jaotusega ning neil on normaaljaotusest pikem vasakpoolne saba. Ainsana ei olnud normaaljaotuse hüpoteesi võimalik ümber lükata ökonomeetrilise intressimäära kestvusmudeli kuise lisatulususe statistilise jaotuse juures.

Mudelite kombineerimine kinnitas aktiivse investeerimise seaduse paika-pidavust: kõigi kolme portfelli koostamise meetodi puhul oli kogu investeeri-misportfelli tulususe ja riski suhe mitu korda parem kui üksikutel mudelitel. Erinevate mudelitele kombineerimine portfelliteooria alusel andis annualisee-ritud *Sharpe*'i suhteks 2,41, leptokurtilise portfelliteooria alusel 2,22 ning kaubeldavate instrumentide arvu alusel 2,09. Antud suhted on üle nelja korra paremad aktiivsete valuutaportfellide haldurite keskmisest annualiseeritud *Sharpe*'i suhtest (0,5), üle viie korra paremad aktiivsete arenevate riikide võla-kirjaportfellide haldurite annualiseeritud *Sharpe*'i suhtest (0,4) ning üle kümne korra paremad aktiivsete globaalsete võlakirjafondide annualiseeritud *Sharpe*'i suhtest (võrdlusandmestiku allikas Collins jt 2005, lk 76). Samuti on doktori-töös koostatud investeerimisportfellide annualiseeritud *Sharpe*'i suhted ligi 8 korda paremad lisatulususe annualiseeritud *Sharpe*'i suhtest (0,27, autori arvutus), mis oleks saavutatav pikaajalise passiivse investeerimisportfelli hoidmisel deposiidiintressi asemel laiapõhjalises aktsiaindeksis.

Empiirilise analüüsi tulemustest võib teha alljärgnevad järeldused.

Järeldus 1. Globaalsed võlakirja- ja valuutaturud on seni veel aktiivse investeerimise kasumlikuks rakendamiseks piisavalt ebaefektiivsed. See järeldus tuleneb nii doktoritöö teoreetilisest kui empiirilisest osast. Teoreetilises osas viidati mitmetele valminud uurimustele, kus mitmesugused aktiivsed investeerimisstrateegiad ei andnud passiivsest osta-ja-hoia-strateegiast statistili-selt oluliselt paremat tulemust. Samas olid need uurimused valminud peamiselt aktsiaturgude andmestikku kasutades. Varasemates teoreetilistes käsitlustes on välja toodud ka hüpotees, et suhteliselt suuremate mittespekulatiivsete raha-voogude osakaalu tõttu võib aktiivse investeerimise meetodite kasumlikkus võlakirja- ja valuutaturgudel olla aktsiaturgudega võrreldes suurem. Empiirilises osas hinnatud mudelite head riski ja tulususe suhted, eriti aga lihtsate ühe-faktoriliste ning struktuurseid riskipreemiaid sisendina kasutatavate mudelite head tulemused näitavad aktiivse investeerimisega lisakasumi teenimise

võimalikkust võlakirja- ja valuutaturgudel. Seda järeldust kinnitab ka autori poolt hallatava Eesti Panga aktiivse investeerimise portfelli (mis kasutab sisendina osaliselt käesolevas töös toodud mudelite signaale) tegelik annualiseeritud *Sharpe*'i suhe perioodil 2003. a jaanuar – 2006. a detsember 1,38.

Järeldus 2. Parema kogutulususe saavutamiseks on võlakirjaturgudele investeerival investoril osa investeerimisportfellist aktsiaturule paigutamise asemel kasulikum võtta tuletisinstrumentide abil aktiivselt valuuta- ja intressiriski. Niisugust järeldust toetab doktoritöös kirjeldatud tuletisinstrumentidega valuuta- ja intressiriski võtva aktiivse investeerimisportfelli parem lisatulususe ja -riski suhe (annualiseeritud *Sharpe*'i suhe üle 2,0-i), võrreldes lisatulususega, mis oleks saavutatav lühiajalises deposiidis hoitava investeerimisportfelli investeerimisega laiapõhjalisse aktsiaindeksisse (annualiseeritud *Sharpe*'i suhe 0,27).

Järeldus 3. Aktiivse investeerimisega stabiilse lisatulu teenimiseks on oluline mitme vähekorreleeritud investeerimissignaali (-mudeli) kombineerimine. Seda järeldust toetab teoreetilises osas kirjeldatud aktiivse investeerimise seadus ning empiirilises osas läbiviidud erinevate mudelite kombineerimine ühtseks investeerimisportfelliks, mis näitas, et kogu portfelli tulususe ja riski suhe on palju parem üksikute mudelite tulususe ja riski suhtest.

Järeldus 4. Valuuta- ja intressiturgudel on turgudevahelised seosed, õige teoreetiline tagapõhi ning majandusnäitajate kaasamine kokkuvõttes paremat tulusust andev, kui ainult finantsinstrumentide hinnaaegridade baasil sobiva tehnilise analüüsi meetodi või ARMA mudeli väljatöötamine. Niisugust järeldust toetasid libisevatel keskmistel baseeruvate mudelite ja ARMA mudelite suhteliselt kehvemad testitulemused, võrreldes ülejäänud testitud mudelitega.

Järeldus 5. Erisuguste investeerimismudelite kombineerimisel ühtseks portfelliks ei anna keerulisemate meetodite (portfelliteooria vms) kasutamine lihtsate optimeerimata meetoditega võrreldes statistiliselt oluliselt paremat tulemust. Seda järeldust toetas kolme investeerimismudelite portfelli (kombineeritud portfelliteooria abil, leptokurtilise portfelliteooria abil ja fikseeritud optimeerimata kaalusid kasutades) võrdlevanalüüs, mis näitas küll portfelliteooria abil kombineeritud portfelli paremat tulusust, kuid tulususe erinevus naiivse portfelli tulususest ei olnud statistiliselt oluline.

Järeldus 6. Väide, et leptokurtilise portfelliteooria kasutamine võimaldab tavalise portfelliteooriaga võrreldes koostada portfelli, milles järsu ja suure kaotuse tõenäosus on väiksem, ei leidnud doktoritöös toetust. Nii kaotus halvimal kuul kui ka suurim järjestikune kaotus olid simulatsioonides leptokur-

tilise portfelliteooria abil koostatud mudelite portfellis suuremad kui tavalist portfelliteooriat kasutades koostatud mudelite portfellis.

Empiirilisel analüüsil väljatöötatud investeerimisportfelli kasutamise võimalused on väga laiapõhjalised, sest tuletisinstrumentide kasutamine annab võimaluse valida portfelli riskiaste täpselt vastavalt investori riski ja tulususe eesmärkidele. Kõige paremini sobib väljatöötatud portfell suhteliselt väiksemate piirangutega riskifondidele. Samas, rangete riskipiirangute olemasolul võivad väljatöötatud mudelportfelli kasutada lisatulu teenimiseks isegi konservatiivsed investorid, nagu keskpangad, kindlustusseltsid ja pensionifondid.

Teoreetilised ja praktilised piirangud uurimistulemuste kasutamisel ja soovitusi tulevasteks uuringuteks

Peamine piirang doktoritöös väljatöötatud mudelite kasutamisel on reaalne oht, et minevikuandmete põhjal testitud mudelite tulusus võib reaalsel investeerimisel järsult halveneda. Seda võib tingida nii uute turuosaliste lisandumisega kaasnev turgude efektiivsuse tõus kui ka minevikuandmetel hinnatud seoste võimalik paikapidamatus tulevikus.

Et mudelid on mõeldud investeerimisvaadete võtmiseks tuletisinstrumentide abil, siis on võimenduse kasutamisel reaalne oht kaotada kogu algkapital. Samuti on töös testitud mudelite tehingukulude arvestamisel lähtutud suurele institutsionaalsele investorile pakutavatest kauplemistingimustest. Eelnevast tulenevalt ei sobi väljatöötatud mudelportfell väikese kapitaliga investorile. Väljatöötatud investeerimismudelid ei sobi ka investorile, kellel töös käsitletud investeerimisvaadete võtmine või töös kasutatud tuletisinstrumentide kasutamine ei ole riskipiirangute tõttu lubatud.

Töös väljatoodud investeerimisotsuste hajutatuse kasulikkus ning finantsturgude dünaamilisus ja turgude efektiivsuse pidev tõus toovad välja kaks suunda võimalikeks tulevasteks uuringuteks. Esiteks on vajalik väljatöötatud investeerimismudelite pidev monitooring, eesmärgiks tuvastada võimalikult varakult mudelid, mille tulusus erinevatel põhjustel on järsult langenud. Seejärel on vajalik tulususe languse põhjuste süvaanalüüs ning mudelportfelli korrigeerimine lähtuvalt analüüsi tulemustest.

Teiseks tulevaseks uurimissuunaks oleks mudelportfelli tulususe parandamine veelgi suurema hajutatuse läbi. Lisaks otsesele tulususe parandamise eesmärgile saavutatakse nii ka olukord, kus erisugustel põhjustel portfellist väljalangenud investeerimismudeli asemel oleks olemas uus, läbitestitud mudel. Väljatöötatud mudelportfelli veelgi suurema hajutatuse saavutamise võimalused oleksid alljärgnevad.

- Laiendada kasutatavate turgude hulka, näiteks kaasata väiksemate arenevate riikide valuuta- ja võlakirjaturud. Samas võib see kaasa tuua tehingukulude suurenemise.

- Laiendada kasutatavate instrumentide ja riskiklasside hulka. Näiteks võimaldaks optsioonide kasutamine võtta turu volatiilsuse muutumise riski jne.
- Laiendada investeeringute horisonti. Doktoritöös väljatöötatud peamiselt kuuajalise sammuga investeerimisvaateid võtvaid mudeleid sobiks täiendama mõni lühiajalisemaid (näiteks päevasiseseid) investeerimisvaateid võttev mudel.
- Laiendada varaklasside hulka, lisades doktoritöös käsitletud valuuta- ja võlakirjaturgudele toormeturu, aktsiaturu, kinnisvaraturu vms.

Lisaks kvantitatiivse mudelportfelli laiendamisele võib investor kaaluda investeerimisotsuste hajutamist ka subjektiivsete investeerimisotsuste lisamise abil või investori positsioonidega vähekorreleeritud positsioone võtva välise portfellihalduri palkamise abil.

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