Financial Internet Quarterly „e-Finanse" 2018, vol. 14/ no. 4, s. 36-55
DOI: 10.2478/fiqf-2018-0026

INVESTMENT STRATEGIES THAT BEAT THE MARKET. WHAT CAN WE SQUEEZE FROM THE MARKET?

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Abstract

The paper presents a new approach to optimizing automatic transactional systems. We propose a multi-stage technique which enables us to find investment strategies *beating the market*. Additionally, new measures of combined risk and returns are applied in the process of optimization. Moreover, we define new elements of a risk control system based on volatility measures and consecutive signal confirmation. As a result, we formulate three complex investment systems which maximize returns and simultaneously minimize risk in comparison to all other alternative investments (*IR=2, Maximum Drawdown<21%, Maximum Loss Duration=0.75 year*). Our analysis is based on historical daily data (1998-2010, in- and out-of-sample period) for index and commodity futures. Afterwards, the systems are reoptimized and reallocated each half a year in order to include the most recent financial data. Finally, we show the results for a joint model consisting of our three systems.

JEL classification: G14, G15, C61, C22
Keywords: investment strategies, automatic trading systems, optimization, technical and fundamental analysis, market volatility, efficient risk and return measures, EMH, mutual and hedge funds,

Received: 20.02.2017 Accepted: 20.12.2018

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The views presented in this text are those of the authors and do not necessarily represent those of Union Investment TFI S.A. or Nest Bank S.A.

Introduction

We observe that fluctuations of prices on contemporary financial markets, which are disrupted by crashes or other turmoil, are much more volatile than in the past. This is one of the reasons why investment techniques (buy&hold strategies, simple portfolio techniques or fundamental analysis) that were the basis of asset management institutions (mutual, pension or hedge funds) for a long time have become less efficient. We notice that contemporary financial markets require more sophisticated investment strategies. Therefore, we observe significant increase in development of automated transactional systems (Chlistalla, 2011) which are the basis of investment activity of financial institutions.

The development of these systems has many causes. On the one hand, computational speed and the amount of data that has to be handled by a decisionmaker are not significant problems since access to fast computing processors, programming environment, and general techniques of data handling is widespread. On the other hand, decisions made by the fund manager or even by investment committee have to rely on numerous, often sophisticated, analyses and indications of various statistics. Such an approach is fundamentally close in its nature to the automated transactional systems called ATS in the later stage of the paper. Putting the decision process into a well-described and defined scheme should lead to better results due to the lack of human subjective opinion bias. This does not change dramatically whether we use ATS based on daily data or if we want to use high frequency (HF) trading systems in order to replicate some intraday patterns in financial market fluctuations. An additional dimension of the issue is that the financial market globalization process forces investors to solve the problem of interpretation of an increasing number of financial market phenomena simultaneously.

All these facts enable us to set up our initial hypothesis that automated transactional systems will play an increasingly significant role in the investment decision process. Technology development, especially growing computation speed and ability to handle a larger amount of data, will benefit institutions that apply automated transactional systems in their investment strategies. Even more important, in our opinion, is that it will be a continuous process in terms of research on the adaptation of developed systems to the rapidly changing environment. This process should be well-defined and incorporated in the ATS construction methodology since it is one of the most important criteria of ATS stability across time.

International markets have witnessed increasing interest of practitioners from financial institutions as well as academics on the subject of employing automated transactional systems for investment decision processes. It has driven us to undertake attempts of verifying hypotheses that are fundamental for this process. We defined one main hypothesis that is related to a few additional supportive questions.

The basic goal is to verify the following research question: **Can we create investment systems beating the market in a consecutive manner independent of cyclically occurring market turmoil?** The investigations of ATS allowed us to define these additional research questions:

1) What kind of criteria work out the best in the process of verification and testing of investment strategies? Which of them are the most important in terms of efficiency of final results?
2) What kind of modification improves efficiency of such systems in practice and in theory?
3) What kind of modification is necessary in standard transactional systems in order to implement them on the market? How often should systems be reoptimized and rebalanced in practice?
4) Is there really a place on the market for conventional stock mutual funds assuming increasing pressure from more effective alternatives?

Additionally, we highlight other important issues that are only partly answered within this research. We indicate them just to shed more light on the problem which potential investors will surely face during the process of development and implementation of automated transactional systems. The issues are listed below:

1) How frequently should the system be reoptimized to incorporate the impact of new data on the shape of a system's formula?
2) The importance of cash management within the automated transactional system and its impact on an investment's efficiency increase.
3) How to deal with the gaps in the prices of futures time series when optimizing the systems?
4) Which of the available alternative financial instruments should we choose for a particular market/

signal? Should we concentrate on futures or options?

The main hypothesis and research questions defined above finally lead us to propose the specific methodology of ATS construction and testing that should be a part of the automated systems implementation process and investment strategy. The structure of this paper is set in order to verify the main hypothesis and find answers to the research questions. After introduction in the first section we come to the literature review. Then in the third section we describe the methodology and data which are followed by the results in the fourth section. The fifth section concludes.

Literature Review

The question of whether financial assets prices are predictable has a long history. The hypothesis has been tested on various assets (stocks and indices, commodities, currencies, and futures), different markets (emerging and developed) using many strategies (technical analysis, fundamental analysis, macro-econometric models, etc.). Generally, we may state that all studies presenting evidence of price predictability assume negation of a weak- and/or semi-strong form of the Efficient Markets Hypothesis.

A broad review of studies about profitability of technical trading strategies can be found in an excellent paper by Park and Irwin (2007). The authors divide the empirical literature into two groups: 'early' and 'modern' studies. **Early studies** (published in the period of 1960-1987) concern testing of several technical trading strategies, among them filters (Fama & Blume, 1966; Sweeney, 1986), stop-loss orders (Houthakker, 1961; Gray & Nielsen, 1963), moving-averages (James, 1968), channels (Irwin & Uhrig, 1984), momentum oscillators (Smidt, 1965) and relative strength (Jensen & Benington, 1970). A general conclusion from this group of studies is that technical trading strategies can generate profits in foreign exchange markets and futures markets (Smidt, 1965a; Stevenson & Bear, 1970; Leuthold, 1972; Cornell & Dietrich, 1978; Dooley & Shafer, 1983; Irwin & Uhring, 1984; Sweeney, 1986; Taylor, 1986), but not in stock markets (Fama & Blume, 1966; Van Horne & Parker, 1967; 1968; James, 1968; Jensen & Benington, 1970). However, there are some limitations in the testing procedures used. Early studies consider only two trading systems, they often ignore the risk of trading rules, no statistical tests of return significance are performed and also the data snooping problem is ignored. Additionally, usually no parameter optimization and no out-of-sample verification are conducted. This was one of the reasons why we paid strong attention to these issues in our research.

On the other hand, **modern studies** (1988-2004) improve significantly upon limitations of early studies. However, there are still present some relevant problems concerning profitability testing methodologies: data snooping, ex-post selecting of investing strategies, and difficulties in risk assessment and estimating of transaction costs. Generally, modern studies prove that technical analysis is profitable in several markets. Among a total of 95 modern studies analyzed, 56 of them find technical analysis to be profitable, and 20 do not. Mixed results are reported in 19 studies. For three market categories, i.e. stock markets (Brock, 1992; Mills, 1997; Bessembinder & Chan, 1998; Raj & Thurston, 1996; Ito, 1999; Coutts & Cheung, 2000; Taylor, 2000; Gunasekarage & Power, 2001), foreign exchange markets (Taylor & Tari, 1989; Taylor, 1992l; 1994; Levich & Thomas, 1993; Silber, 1994; Szakmary & Mathur, 1997; LeBaron, 1999; Olson, 2004) and futures markets (Lukac et. al., 1988, Lukac & Brorsen, 1990; Bessembinder & Chan, 1998; Sullivan, 1999; Sullivan, 2003; Wang, 2000; Nelly, 2003), the majority of results support the hypothesis of the predictability of technical trading strategies.

Park and Irwin (2007) also provide detailed discussion about **possible explanations for technical trading profits**. They can be described as theoretical and empirical. In theoretical models, technical trading profits may arise because of market 'frictions', such as noise in current equilibrium prices and traders' sentiments (Hellwig, 1982; Brown & Jennings, 1989; Grundy & McNichols, 1989; Blume et al., 1994) or herding behavior (Froot et. al., 1992; Schmidt, 2002), market power or chaos (Clyde & Osler, 1997; Stengos, 1996). On the other hand, empirical explanations focus on technical trading profits as an effect of central bank interventions (Dooley & Shafer, 1983; Sweeney, 1986l; Lukac et. al., 1988; Silber, 1994; and more recently: Szakmary & Mathur, 1997; LeBaron, 1999; Neely & Weller, 2001; Neely, 2002; Saacke, 2002; Sosvilla-River et. al. 2002; Sapp, 2004), order flow (Osler, 2003; Kavajecz & Odders-White, 2004; Gehrig & Menkhoff, 2003; 2004), temporary market inefficiencies (Sweeney, 1986; Taylor, 1986; Lukac et. al., 1988; Brock, 1992; Sullivan, 1999; 2003; Olson, 2004; Kidd & Brorsen, 2004), risk premiums

(Lukac & Brorsen, 1990; Kho, 1996; Chang & Osler, 1999; LeBaron, 1999; Sapp, 2004) and market microstructure deficiencies (Greeer, 1992)

In more recent study, Dunis et al. (2010) provide evidence of contrarian returns, using the information contained in open-to-close (days) and close-to-open (night) periods, rather than the more frequently used close-to-close period. The authors show that the strategy of buying worst performing shares during the day and holding them during the night generates a significant alpha and its returns cannot be explained by the 3-factor model of Fama and French (1993) or 5-factor model of Carhart (1997). These results support evidence of profitability of mean reverting strategies in previous studies (Jegadeesh, 1990; Lehman, 1990; Forner & Marhuenda, 2003; Choi & Jayaraman, 2009; McInish et. al., 2008; Serletis & Rosenberg, 2009; Leung, 2009). To some extent, contrarian profits can be explained by the overreaction hypothesis (Lo & MacKinlay, 1990). Another study of Hameed et al. (2010) shows that return reversal effects are strong and pervasive also at intra-industry level, even when adjusted for exposure for common risk factors in Fama and French (1993). Similar results were obtained by Da et al. (2010).

Another strand in the literature constitutes studies testing investment strategies based on factor loading or a fundamental approach. Examples are studies of Fama and French (1992) or Daniel and Titman (1997) and strategies based on price-to-earnings ratio (Basu, 1977; Danielson & Dowdell, 2001), price-to-dividends ratio (Campbell & Schiller, 1998), market-to-book value or company size (Banz, 1981; Jagannathan & Wang, 1993). Other studies provide evidence that company capital structure can be used as a predictor of abnormal returns (Bhandari, 1988; Hull, 1999; Ghosh & Cai, 1999; Korteweg, 2004). In a more recent study, Baturevich and Muradoglu (2010) find that the long run relationship between leverage and stock returns can be used to build a profitable trading strategy and that investing in low-debt companies yields significant abnormal returns.

A separate group of articles are those **evaluating performance of the hedge fund industry**. Assessing this performance is a relatively difficult task because of the complex and diverse investing strategies used by fund managers. It seems that the Sharpe ratio and the Treynor ratio are two simple and common measures of risk-adjusted performance of hedge funds (Gehin, 2004). In order to identify risk-adjusted performance usually popular asset pricing models are used. These can be the CAPM single-factor model (Sharpe, 1964), Fama-French (1993) three-factor model, four-factor model of Carhart (1997) and their several extensions allowing for company size, PE and book-to-market ratios, dividends and momentum effects. There is some evidence that hedge funds outperform other investment strategies (Ackerman, 1999; Liang, 1999; Eling, 2006), although some researchers emphasize some methodological problems: autocorrelation in returns (Lo, 2002), leptokurtic return distributions (Eling, 2006) or the fact that returns can be affected by survivorship bias and backfill bias (Park et al., 1999; Fund & Hsieh, 2000, Capocci & Hübner, 2004). On the other hand, Sandvik et al. (2011) report results based on a relatively long period (1994-2009) and several investing strategies indicating that the hedge fund industry fails to create significant alpha.

As a final note, it has to be emphasized that results from studies answering the question of whether financial assets prices are predictable (especially profitability of technical trading systems) may be to some extent subject to "**publications bias**". This occurs when the researcher, having identified a way to beat the market, has little incentive to publish his methodology in detail in academic journals and simultaneously may be willing to sell it to some investment banks. As a result, we may have a good reason to believe that evidence of asset prices predictability can be somewhat "underestimated".

Methodology and data

Data description

Data applied in the research cover the period from 1998 to 2010. All analyzed time series are based on daily intervals. All data were downloaded from Polish data provider www.stooq.pl. The following instruments were utilized in the analysis:

1) continuation time series for WIG20 index futures (single futures time series were changed based on maximum open interest) - I_system_fw20,

2) stock indexes, and futures on stock indexes and commodities, e.g.: RTS index, PX50 index, platinum futures, gold future, cotton futures – II_system_high-low_USD,

3) continuation time series for DAX index futures – III_system_daxfuture_EUR,

4) risk free rate in Poland, USA and Germany,

Additionally, we used data for financial instruments included in benchmarks:

1) WIG index, ARKA Akcji FIO mutual fund, OFE ING NN pension fund,

2) Gold spot, Bovespa index, S&P500 index,

For research purposes time series were split into two subsamples dividing the sample into in-sample period and out-of-sample period as follows:

1) in the case of optimization (I_system and III_system):

a) *in-sample*: I.1998-XII.2009 (I_system),

b) *in-sample*: IX.1998-XII.2009 (III_system),

c) *out-of-sample*: I-XII.2010 -> it was a very challenging year for all financial institutions relying on ATS because of a long lasting horizontal trend,

In the case of II_system, where no optimization process was applied, the whole period i.e. I.1999-XII.2010, was subjected to a backtesting procedure. However, the results were split into two subperiods in order to compare them with the out-of-sample results for I_system and III_system.

Theoretical background

Searching for the answer to our main question defined in the previous chapter we made an assumption related to the Efficient Market Hypothesis. Literally, we assumed that information included in the past prices is valuable in the process of prediction of their futures prices. This assumption is in obvious contradiction to a version of EMH in the information sense. This approach directs us towards practical usage of one of the investment techniques i.e. automated transactional systems which has been widely researched in recent years, mainly by mutual and hedge funds. However, there are not many research results revealed to the public. Our goal is to investigate the areas that have the most significant impact on ATS performance. To analyze the most sensitive areas we decided to go through the whole process of ATS construction paying special attention to risk management on all levels of ATS construction.

There are two main streams that present two different approaches to construction of ATS: the optimization-based selection and expert-based selection type. The first relies on a defined, iterative process of selecting the most effective concept and parameters of the system for out-of-sample period using only in-sample data. Then the best systems are verified on the out-of-sample period to assess the stability of achieved results. The aim of optimization is to find the best version of the investment system through adjusting of buy/sell/stops algorithms to historical prices taking into account given boundary conditions (presented in detail in Table 1).

The second approach uses a human expert selection process of the ATS formula which requires the experience of the researcher in practical investment. Then selected ATS are backtested on the whole available period. The aim of backtesting is to verify whether the formulas found in the expert way are valid on a historical time series. We applied both approaches in our research: first – an optimized approach for I_system and III_system and second – an expert one for testing of the II_system concept.

At the beginning of the ATS construction process, we tried to define a few conceptual aims that are easily translated into the practice of investment world. These goals helped us to focus our attention on the most important and sensitive areas. The aims are as follows:

1) to define investment systems which can make a profit on various financial markets (equity, commodities, currencies or interest rates) independently of actual market conditions (upward, downward or horizontal trends) and regardless of current macroeconomic cycle phase,

2) to find investment systems maximizing annual compound rate and minimizing risk in comparison to all other alternative investments (in the period of the last 12-13 years),

3) to minimize the liquidity risk through investments on various markets considering their volume of turnover and open interests, or level of development (emerging and developed markets),

4) to define a risk management system already on the level of setting the optimal size of an open position for each trade.

The description of final systems

The analysis of the above aims drove us to define the main steps of the process of ATS construction. Some of them, like risk management and system monitoring, play a crucial role in the efficiency of the final ATS selection.

The below mentioned steps helped us to find systems that reach our investment goals:

1) looking for investment algorithms (technical analysis indicators, fundamental analysis, macro models, econometric models, etc),

2) testing and finding the final version of the system, based on the final version of each of the strategies (I_system and III_system) or the composition of one system for n-different financial instruments (II_system),

3) in the case of optimization (I_system and III_system) we find the final version of the system on the basis of in-sample data optimization for each of the strategies separately:

$$\underset{x_1,\dots,x_i}{Max}(indicator_j) \tag{1}$$

$$indicator_j = \frac{NP_j}{SE_j^{EqLine}} \tag{2}$$

where:

$x_1,\dots,x_i$ - different parameters for each of the strategies set in the process of optimization,

j - the number of the strategy (from 1 to 8) which is the part of investment system,

NP_j - net profit of the *j*th strategy,

SE_j^{EqLine} - standard error of equity line of the *j*th strategy,

4) in the case of expert formulas, we only backtest the system on in-sample data in order to check the system performance on historical data,

5) setting the number of open positions for each system based on the cumulative single results from the set of strategies ($L_t^{optimistion}$ for I_system and III_system) or actual risk level compared with the historical one ($L_t^{backtest}$ for II_system),

$$L_t^{optimisation} = \sum_{j=1}^{8} result_{j,t} \tag{3}$$

$$L_t^{backtest} = \frac{EqLine_{t-1}}{Close_{t-1}} * RF * \frac{1}{SF_{t-1}} \tag{4}$$

$$SF_t = if \begin{cases} \left(\frac{RV_t^{3m}}{HV_t^0}\right)^2, for & \left(\frac{RV_t^{3m}}{HV_t^0}\right)^2 > 1 \\ 1, \quad for & \left(\frac{RV_t^{3m}}{HV_t^0}\right)^2 \le 1 \end{cases} \tag{5}$$

where:

t - the number of the consecutive day,

$result_{j,t} = \{-1,0,1\}$ - the results of buy/sell/stop algorithm for the *j*th strategy on day *t*,

$EqLine_t$ - the value of equity line for day *t*,

$Close_t$ - close price for financial instrument on day *t-1*,

RF - the risk factor set on the level of 2,

SF_t - the scaling factor decreasing the number of open position when actual volatility sharply increases,

RV_t^{3m} - the actual volatility calculated as realized volatility on the basis of 3-month price history,

HV_t^0 - the historical volatility calculated as the standard deviation of returns on the basis of data from the first day to day *t*,[1]

6) Risk monitoring of the system on out-of-sample data and comparing it with the average and extreme results from in-sample data, in order to switch off the parts (one of the systems in case of the final joint system or one of the strategies) of the system which exceed the defined risk limits,

$$\begin{gathered} if \quad y_i \quad > \quad y_{i'}, i = 1,\dots,k \Rightarrow \\ \Rightarrow switch \quad off \quad \& \quad reconstruction \end{gathered} \tag{6}$$

where:

$y_1,\dots,y_k$ - risk statistics for out-of-sample period formulated in detail in Table 1,

$y_{1'},\dots,y_{k'}$ - risk statistics for in-sample period,

7) Re-optimization, rebalancing and reconstruction of the system after the given period of time (e.g. half a year),

8) The analysis of results for in-sample and out-of-sample on the basis of daily data for yearly periods in order to estimate the stability of outcomes. Additionally, the data are analyzed in a yearly rolling window.

It is important to note at this place that for most of the time about 10% of our portfolio is allocated to the deposit for different futures contracts used and about 90% remains in cash. Intentionally, we do not take into account the interest on this cash in order to not increase the results and reserve some space for the potential downward bias of our results. Construction of the three finally selected systems are presented below.

I_system_fw20 and III_system_dax-future

In the processes of construction of I_system and III_system the only difference is the underlying asset. I_system is based on futures contracts on the WIG20 index of Warsaw Stock Exchange (FW20), while III_system uses futures contracts on the DAX index of Deutsche Borse (Dax future). Detailed description of both systems is listed below:

1) The combination of 8 various transactional

1 The detailed explanation of calculation formulas for RV and HV can be found for example in Ślepaczuk and Zakrzewski (2009),

strategies[2] based on technical analysis and statistical measures for one of the financial instruments respectively: FW20 (I_system), Dax future (III_system):

a) I strategy: LRS – the combination of simple statistical tools,

b) II strategy: OSC – the combination of different technical analysis oscillators,

c) III strategy: MACD – moving average crossover divergence,

d) IV strategy: SMA – simple moving average,

e) V strategy: TEMA – triple exponential moving average,

f) VI strategy: RSI – relative strength index,

g) VII strategy: CCI – commodity channel index,

h) VIII strategy: HLV - high-low values crossover,

2) Strategies generate mid-term buy/sell/stop signals,

3) Every strategy is separately optimized on in-sample data,

4) Variable capital allocation considering the size of open position on the level of the system. Single signals from each strategy are aggregated in order to define the direction and transactional unit on the level of the system (formula 3),

5) Finally, based on the boundary conditions calculated on the basis of in-sample period (summarized in Table 1) we set financial leverage, risk factor and initial equity at a level which enables us to maximize annual compounded return (ARC),

6) This system is easy to replicate for different financial instruments like stock indexes (e.g. RTS, Bovespa, KLSE, and PX50), commodities, bonds, and currencies.

II_system_high-low

One of the main differences between the systems described above and II_system is lack of an optimization process in terms of formula selection for the latter. The construction of this system is summarized below:

a) The investment algorithm is based on crossover of the reference price recorded n-days ago (non-optimized algorithm and the same for each financial instrument). It is applied for various financial instruments (stock indexes, commodities and futures), e.g.: CRB futures, Gold futures, Shanghai composite index, RTS index, DAX futures, Cotton futures, ATGI index, Platinum future, etc.

b) System generates long-term buy/sell signals,

c) No optimization applied in the selection process, only backtesting,

d) Variable allocation considering the size of open position. The algorithm set the transactional unit based on the comparison of actual and historical volatility (formula 4),

e) Finally, based on the boundary conditions calculated on the basis of in-sample period (summarized in Table 1) we set financial leverage, risk factor and initial equity on the level which enables us to maximize annual compounded return (ARC),

f) Periodic reallocation of funds between each financial instrument within the system (e.g. each half a year).

Statistics used to evaluate the performance and the boundary conditions

In the literature one can find many various measures of the efficiency of ATS. These measures are used in order to assess the performance of ATS and finally choose the best one to be used in the future. The problem is that mostly we refer to profitability measures than to risk measures. In reality, it affects our selection process in such a way that we choose the most profitable system. This produces highly volatile results, which are not persistent in the out-of-sample period. Therefore, we focused rather on risk than profitability measures in the process of selection of the optimal version of strategies and then systems. To provide complex assessment of the presented systems we also calculated a wide range of measures. They relate to three dimensions: profitability, risk, and a third area covering statistics that combine risk and profitability. The applied statistics with short definitions are listed below:

1) **aSD** – Annual Standard Deviation – annualized standard deviation calculated in the standard way,

$$aSD = \sqrt{252} * \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(R_t - \bar{R})^2} \tag{7}$$

where:

R_t - logarithmic rate of return,

2) **5%-VaR** – Value at Risk at 5% - Value at Risk measure (5th percentile on the daily data) calculated on the basis of historical daily returns,

3) **maxFL** – Maximum Financial Leverage – maximum level of financial leverage used in the testing period; 33% means leverage on the level of 1:3,

2 Detailed description of signal generation by the given buy/sell/stop algorithm can be found for example in Murphy (1999) or Ślepaczuk (2006).

4) **MD** – Maximum Drawdown – maximum level of drawdown in the testing period, where drawdown identifies the distance of equity line (measured in percentages) between the previous local maximum to the forthcoming local minimum [3]:

$$MD = \underset{i=1,\ldots,t;\, t=1,\ldots,N}{Min} \left(\sum_{j=i}^{t} R_j\right) \tag{8}$$

where:

Rj - logarithmic return on day j,

5) **AMD** – Average per year Maximum Drawdown – the average yearly maximum drawdown in the testing period,

$$AMD = \frac{1}{n}\sum_{i=1}^{n} MD_i^{yearly} \tag{9}$$

where:

MD_i^{yearly} - yearly maximum drawdown calculated for each year separately,

n - number of years under investigations,

6) **MLD** – Maximum Loss Duration (in years) – informs us about maximum number of years, between the previous local maximum to the forthcoming local maximum,

$$MLD = Max\frac{n}{252} \quad where \quad \begin{cases} n = m_j - m_i \\ Val_{m_j} > Val_{m_i} \\ j > i \end{cases} \tag{10}$$

where:

m_j, m_i - the number of days indicating consecutive local maximum of equity line,

Val_{m_j}, Val_{m_i} - values of local maximums in day m_j and m_i,

7) **Correlation** – correlation coefficient – coefficient reflecting the correlation of rates of return between the given system and the market; I_system with WIG20 futures, II_system with S&P500 futures, and III_system with DAX futures,

8) **AllRisk** = aSD*MD*MLD*AMD*1000 – aggregated measure of risk reflecting risk of the system as a product of 4 basic risk measures used in the process of designing of automated transactional systems,

$$AllRisk = aSD * MD * MLD * AMD * 1000 \tag{11}$$

9) **ARC** – Annual Return Compounded – calculated in the standard way,

$$ARC = 252 * \frac{1}{N}\sum_{t=1}^{N} R_t \tag{12}$$

10) **Sharpe** – Sharpe ratio – calculated in the standard way as a quotient of difference of annual compounded rate and risk- free rate and annualized standard deviation,

11) **IR** – Information Ratio – indicator calculated as a quotient of annual compounded rate and annualized standard deviation,

$$IR = \frac{ARC}{aSD} \tag{13}$$

12) **ARC/MD** - Annual Return Compounded/Maximum Drawdown – quotient of annual compounded rate and maximum drawdown,

13) **ARC/AMD** - Annual Return Compounded/ Average per year Maximum Drawdown - quotient of annual compounded rate and average per year maximum drawdown.

Risk management is of huge importance in ATS management. Therefore, one of the first steps of the research was to define satisfactory levels of statistics describing system performance (the boundary conditions) for the in-sample period. Using the best available investment alternatives (i.e. long-term results for the best hedge fund classified as quantitative fund managers), we set cut-offs for measures used during selection of final shape of the systems. Obviously, the defined criteria were not the only rules of the selection, and systems were simultaneously subjected to other investigations. However, they were one of the most significant ones. Eligibility criteria for performance characteristics are defined in Table 1 below.

Benchmark strategies

As mentioned previously, to obtain complex assessment benchmarks were selected according to the best results obtained in the in-sample period. As the most intuitive benchmarks for I_system were chosen the following assets:

1) main Polish stock market index WIG index.
2) *ARKA Akcji FIO* mutual fund and
3) *OFE ING NN* pension fund,

For II_system and III_system worldwide best alternatives were considered, i.e. stock indexes, commodities, bonds, and currencies. Finally, three benchmarks were selected:

1) Gold spot,
2) Bovespa index,
3) S&P500 index, as the most profitable alternatives and highly representative.

3 Dunis et al. (2010),

Table 1: Cut-off criteria for statistics (the boundary conditions)

Dimension	Statistics	Criterion
Risk	aSD - Annual Standard Deviation	< 20%
	5%-VaR - Value at Risk at 5%	< 2%
	maxFL - Maximum Financial Leverage	< 33% (the equivalent of 1:3)
	MD - Maximum Drawdown	< 21%
	MLD - Maximum Loss Duration (in years)	< 0.8
	AMD - Average per year Maximum Drawdown	< 14%
	AllRisk = aSD*MD*MLD*AMD*1000	< 3
Profitability	ARC - Annual Return Compounded	> 30%
Risk and Profitability	Sharpe - Sharpe ratio	> 1.5
	IR - Information Ratio	> 1.75
	ARC/MD - Annual Return Compounded/Maximum Drawdown	> 1.5
	ARC/AMD - Annual Return Compounded/ Average per year Maximum Drawdown	> 2.5
	The number of transactions	< x-yearly

* Table 1 presents boundary conditions which were taken into account when searching for the final version of each system on the basis of in-sample period. The boundary conditions set the limit for maximum risk undertaken in the process of investment. They are divided into three sections: maximum values for Risk, and minimum values for Profitability and "Risk and Profitability".

Results

This section presents results for the three systems described previously. Tables with detailed statistics, as well as respective figures, are shown to provide a full view of the achieved performance. For each system results are presented taking into account assumptions, figures and detailed statistics of the system. Results are presented separately for in-sample and out-of-sample periods and are compared to respective benchmarks. Finally, the comparison of the three ATS is presented together with the results for the concept which aggregate three separate systems into one: I+II+III_system.

I system_fw20_PLN

Results for I_system, which utilizes investment algorithms based on basic signals from 8 single strategies, are presented in Table 2. Data were split into two periods: in-sample, which covers 01.01.1998-31.12.2009 and out-of-sample for 01.01.2010-31.12.2010.

Statistics presented in Table 2 met our targets defined in Table 1 (for in-sample period). *annual return compounded* rate reaching 35.2% is a not surprising effect when using optimization. However, in conjunction with annual standard deviation below 20% (19.3%), it indicates substantially better performance than one may expect. Such results are able to be obtained due to application of a multi-stage technique (i.e. buy/sell/stops rules selection, parameters optimization, combining many strategies into one system, cash management and risk management on the level of setting an optimal number of open positions and consecutive reoptimization, reallocation, and reconstruction of the systems). Efficiency of the applied technique is proven by validation results for the out-of-sample period. There are no significant changes in the levels of statistics. The decrease in the *ARC* by 6.2 pp was balanced by decrease in *aSD* by 5.3 pp and three other risk statistics. Finally, *Sharpe ratio* (and IR), which combines risk and return dimension, slightly increased for validation sample to 1.7 from 1.6 (to 2.08 from 1.83).

Figure 1 presenting equity lines was prepared to analyze investment behavior of I_system_fw20 and benchmarks across the whole period. For clarity of analysis, an assumption was made that initial capital equals 1 million PLN. Investigation of the equity lines for I_system and benchmarks confirms conclusions drawn during analysis of the statistics. The linearity of I system equity lines shows that it is possible to create sustainable performance over a long period. Especially worth mentioning is the resistance of results to the market cycles[4]. I_system creates stable returns regardless of the market direction.

4 We mean recession periods indicated by sharp downward movement of the markets in 2001-2002 and 2007-2009.

Table 2: Performance statistics for I_system_fw20

Statistic name	Abbreviation of statistics	I system_fw20 in-sample and out-of-sample	I system_fw20 out-of-sample
annual return compounded	ARC	35,2%	29,0%
Annualstdev	aSD	19,3%	14,0%
information ratio	IR	1,83	2,08
maximum drawdown	MD	15,2%	9,9%
max financial leverage	maxFL	73%	73%
maximum loss duration (in years)	MLD	0,48	0,32
Sharpe ratio	Sharpe	1,6	1,7
annual return compounded (%) / max drawdown (%)	ARC / MD	2,3	2,9
average per year max drawdown (%)	AMD	9,5%	9,9%
annual return compounded (%) / average per year max drawdown (%)	ARC / AMD	3,7	2,9
Allrisk	allrisk	1,34	0,44

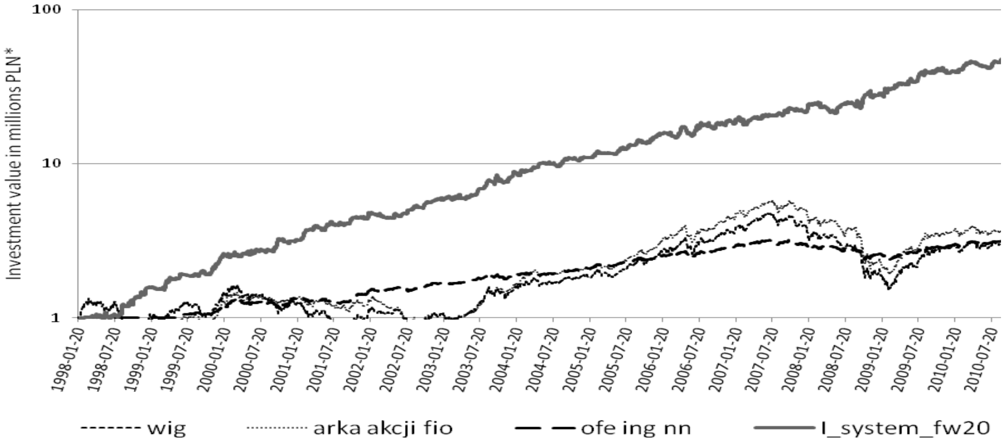
* Table 2 presents performance statistics for I_system_fw20 in two subsamples: in-sample period, which covers 01.01.1998-31.12.2009 and out-of-sample period for 01.01.2010-31.12.2010.

Table 3: Performance statistics for benchmarks and I_system_fw20 statistics (in-sample and out-of-sample period)

Statistic name	Abbreviation of statistics	WIG20	Arka akcji FIO	OFE ING NN	I_system _fw20
annual return compounded	ARC	9,8%	11,3%	9,6%	35,2%
Annualstdev	aSD	23,9%	20,1%	6,8%	19,3%
information ratio	IR	0,41	0,56	1,40	1,83
maximum drawdown	MD	68,5%	66,7%	25,6%	15,2%
max financial leverage	maxFL	100%	100%	100%	73%
maximum loss duration (in years)	MLD	3,83	3,4	3,23	0,48
Sharpe ratio	Sharpe	0,2	0,3	0,7	1,6
annual return compounded (%) / max drawdown (%)	ARC / MD	0,1	0,2	0,4	2,3
average per year max drawdown (%)	AMD	37,2%	29,9%	9,2%	9,5%
annual return compounded (%) / average per year max drawdown	ARC / AMD	0,3	0,4	1,0	3,7
Allrisk	allrisk	234,00	136,20	5,22	1,34

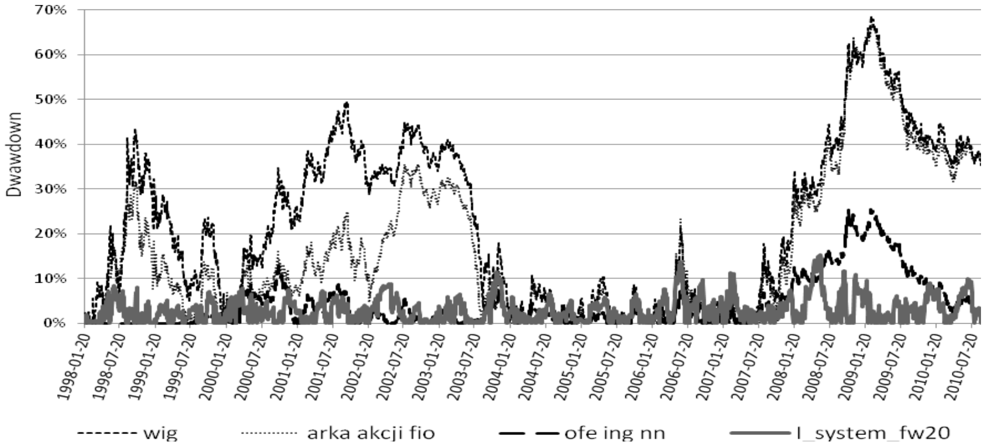
*Table 3 presents detailed statistics for I_system in comparison to the benchmarks from the Polish capital market (WIG index, Arka akcji fio mutual fund and OFE ING NN pension fund).

Figure 1: Equity lines for I_system_fw20 and its benchmarks



* Figure 1 presents equity lines (assuming the initial investment of 1 million PLN) for I_system_fw20 in comparison to WIG index, Arka akcji fio mutual fund and OFE ING NN pension fund in the period: 1998.01.20-2010.12.31. We use logarithmic scale.

Figure 2: Drawdown for I_system_fw20 and the benchmarks



* Figure 2 presents the fluctuations of drawdown for I_system_fw20 in comparison to WIG index, Arka akcji fio mutual fund and OFE ING NN pension fund in the period: 1998.01.20-2010.12.31.

The fluctuations of drawdown for I_system and benchmarks are presented below (Figure 2) in order to analyze in more detail the risk of the investment alternatives. It shows that even OFE ING NN pension fund, which is supposed to be less risky, witnessed higher drawdown during the last crisis 2007-2009 and the crisis after the internet bubble in 2000-2001. I_system_fw20 keeps the drawdown below 15.2%, only a few times exceeding 10%.

Statistics shown in Table 3 confirm better performance of the discussed ATS than any available alternative. It is especially visible when comparing statistics that combine risk and return measures. *Sharpe ratio* for I_system outpaced significantly these for the alternative investments: 1.6 for I_system vs. 0.2, 0.3 and 0.7 for WIG20, Arka akcji FIO, OFE ING NN respectively. When analyzing risk dimension, especially worth underlining is *Maximum Loss Duration*: 0.48 for ATS while for alternatives it varies from 3.23 for OFE ING NN to 3.83 for WIG20 (as numbers of years).

II_system_ high-low_USD

The construction of II_system (II_system_high-low_USD) differs from the methodology used for I_system and III_system. The results are obtained based on one investment algorithm used for *n* various financial instruments. The data sample was split along with the previous methodology into in-sample and out-of-sample in order to assess the stability of achieved results. Statistics for the validation period (out-of-sample) are again worse

Table 4: Performance statistics for II_system

Statistic name	Abbreviation of statistics	II_system_high-low_USD in-sample and out-of--sample	II_system _high-low_USD out-of-sample
annual return compounded	ARC	35,6%	23,0%
Annualstdev	aSD	14,1%	18,0%
information ratio	IR	2,52	1,27
maximum drawdown	MD	20,7%	20,1%
max financial leverage	maxFL	37%	45%
maximum loss duration (in years)	MLD	0,61	0,55
Sharpe ratio	Sharpe	2,4	1,1
annual return compounded (%) / max drawdown (%)	ARC / MD	1,7	1,1
average per year max drawdown (%)	AMD	13,3%	20,1%
annual return compounded (%) / average per year max drawdown (%)	ARC / AMD	2,7	1,1
Allrisk	allrisk	2,37	3,99

* Table 4 presents performance statistics for II_system_high-low in two subsamples: in-sample period, which covers 01.01.1999-31.12.2009 and out-of-sample period for 01.01.2010-31.12.2010.

than for the total sample, but the deterioration does not disqualify this system from further investigations. *Sharpe ratio* reaching level 1.1 and *IR* which equals 1.27 is far above alternative benchmarks. Detailed statistics are gathered in Table 4.

III_system_daxfuture_EUR

Performance statistics for III_system (III_system_daxfuture_EUR) are presented in Table 5. Data, similarly as for I_system, were split into two subperiods: in-sample, which covers 01.19.1998-31.12.2009 and out-of-sample for 01.01.2010-31.12.2010. Out-of-sample statistics show slight deterioration vs. levels from the whole period.

Table 5: Performance statistics for III_system

Statistic name	Abbreviation of statistics	III_system in-sample and out-of-sample	III_system out-of-sample
annual return compounded	ARC	35,3%	21,8%
Annualstdev	aSD	16,2%	21,3%
information ratio	IR	2,19	1,02
maximum drawdown	MD	14,3%	13,9%
max financial leverage	maxFL	41%	30%
maximum loss duration (in years)	MLD	0,79	0,24
Sharpe ratio	Sharpe	1,9	0,8
annual return compounded (%) / max drawdown (%)	ARC / MD	2,5	1,6
average per year max drawdown (%)	AMD	8,2%	7,4%
annual return compounded (%) / average per year max drawdown (%)	ARC / AMD	4,3	3,0
allrisk	allrisk	1,50	0,53

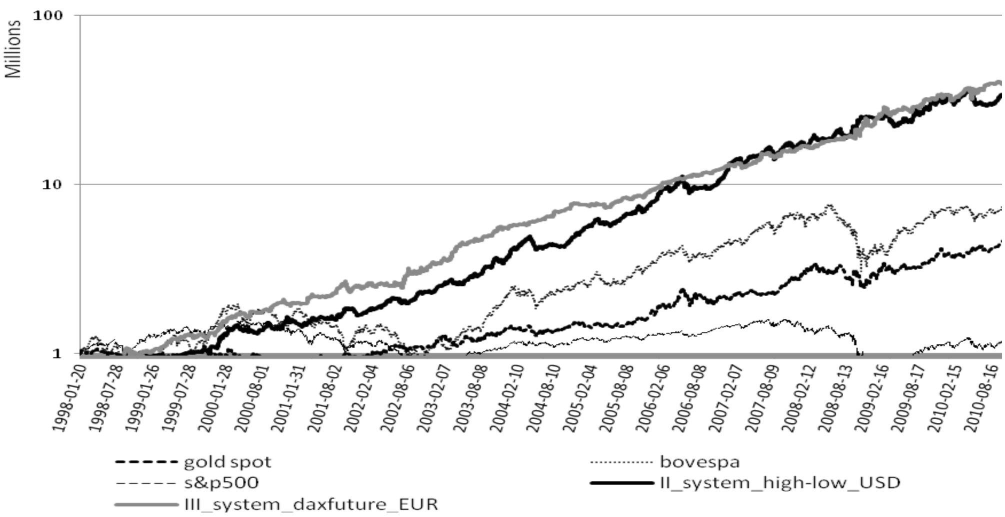
* Table 5 presents performance statistics for III_system_daxfuture in two subsamples: in-sample period, which covers 01.09.1998-31.12.2009 and out-of-sample period for 01.01.2010-31.12.2010.

However, risk and returns of combined measures remain at satisfactory levels (*Sharpe ratio* is on the level of 0.8 and *IR* remains above 1.0).

The performance of the II and III systems and their benchmarks across the whole period is presented on Figure 3. The plots clearly show significantly better results for our two ATS than for alternatives. The outperformance of ATS is visible not only in higher return rates but also in risk statistics i.e. stability of returns. Again, the ATS sustainably survived market downturns, while the comparable benchmarks were severely affected by market crashes. This stability of returns assures us that the applied steps, especially the method of setting the number of open positions based on several subsystems combined into one, allow us to significantly reduce volatility of results while keeping returns on a highly satisfactory level.

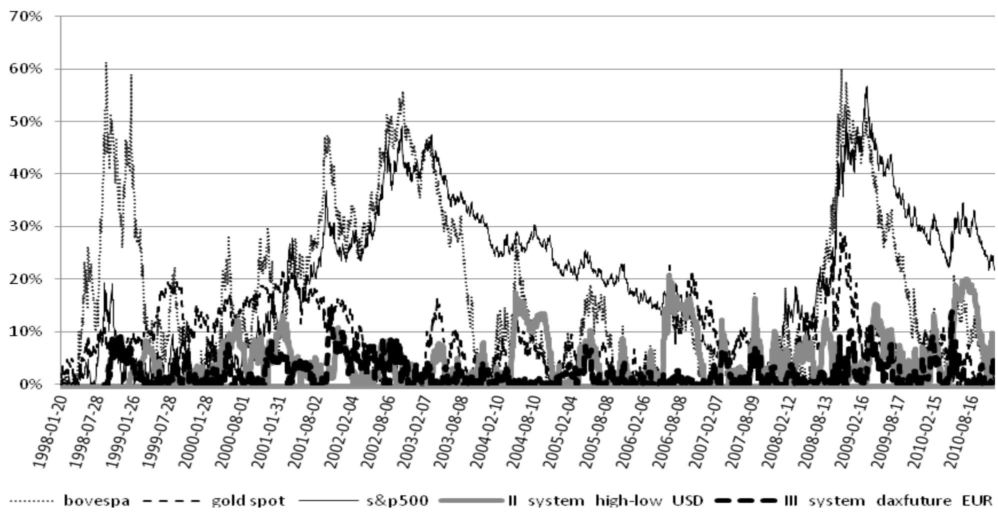
For deeper investigation of the volatility of the results for II and III systems, the comparison of drawdown fluctuations is presented on Figure 4. One can easily notice that the only alternative for which drawdown may be compared to the ATS is gold spot investment. However, moving to the more detailed data in Table 6 we see that even though *Maximum Drawdown* for gold is

Figure 3: Equity lines for II_system, III_system and benchmarks



* Figure 3 presents equity lines (assuming the initial investment of 1 million) for II_system_high-low and III_system_daxfuture in comparison to Gold spot, Bovespa index and S&P500 index in the period: 1998.09.01-2010.12.31. We use logarithmic scale.

Figure 4: Drawdown for II_system, III_system and benchmarks



* Figure 4 presents the fluctuations of drawdown for II_system_high-low and III_system_daxfuture in comparison to Gold spot, Bovespa index and S&P500 index in the period: 1998.09.01-2010.12.31.

Table 6: Performance statistics for system II, III and their benchmarks

Statistic name	Abbreviation of statistics	bovespa	gold spot	s&p 500	II_system _high-low_ USD	III_system _daxfutu-re_EUR
annual return compounded	ARC	16,2%	12,8%	1,9%	35,6%	35,3%
annualstdev	aSD	35,6%	18,1%	21,6%	14,1%	16,2%
information ratio	IR	0,46	0,71	0,09	2,52	2,19
maximum drawdown	MD	61,3%	28,8%	56,8%	20,7%	14,3%
max financial leverage	maxFL	100%	100%	100%	37%	41%
maximum loss duration (in years)	MLD	3,60	2,61	7,14	0,61	0,79
Sharpe ratio	Sharpe	0,3	0,4	-0,1	2,4	1,9
annual return compounded(%)/max drawdown(%)	ARC / MD	0,3	0,4	0,0	1,7	2,5
average per year max drawdown (%)	AMD	39,8%	17,3%	31,6%	13,3%	8,2%
annual return compounded (%)/ average per year max drawdown (%)	ARC/AMD	0,4	0,7	0,1	2,7	4,3
allrisk	allrisk	312,33	23,46	277,00	2,37	1,50

*Table 6 presents detailed statistics for II_system_high-low and III_system_daxfuture in comparison to Gold spot, Bovespa index and S&P500 index in the period: 1998.09.01-2010.12.31.

relatively low, the maximum loss duration is substantially higher than for ATS: 2.6 years for gold vs. 0.6 and 0.8 for systems II and III respectively. It means that II and III system require only 6 and 9 months respectively to reach capital levels observed in the last maximum. Measures combining risk and return also make us confident that the defined process of ATS construction provides the user with results significantly better that the market. *Sharpe ratio, information ratio* and *annual return compounded (%)/average per year max drawdown* presented in Table 6 prove that a defined multi-stage technique will benefit the investor with stability of the system while providing a satisfactory level of return.

I+II+III_system

Investigations presented above in this section allow us to conclude that careful combination of several strategies into one system, and/or several strategies for various financial instruments into one system, results in significant reduction of risk. Finally, having developed three separate systems (i.e. I, II and III), we will analyze the conjunction effect of applying the system as a single investment portfolio[5]. Two general assumptions have to be made for the purpose of the analysis. First, an equal amount is invested into each of three systems. The second assumption is made with regards to different currency issues. We assume that all currency risks are fully hedged, so that we may focus only on adequate recalculation of returns.

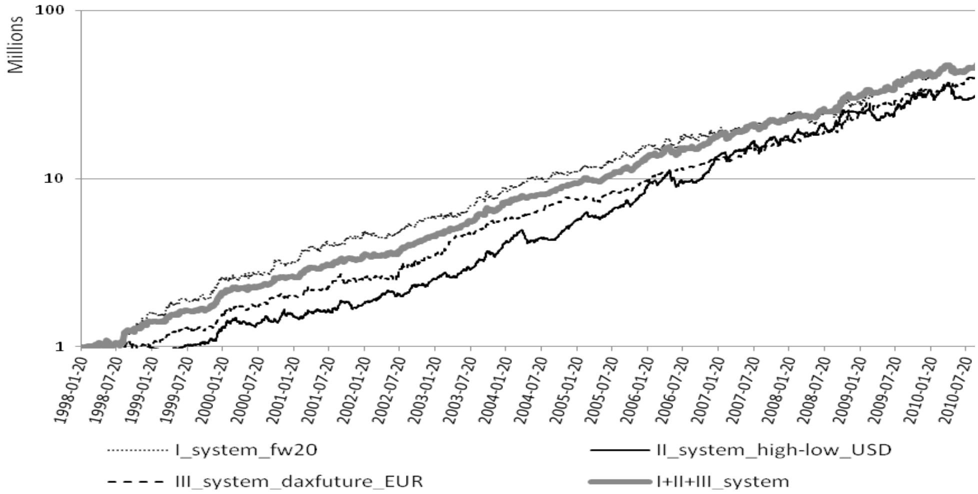
This final step delivers a complex system (I+II+III_system) that in terms of risk and return measures outperforms its components. Figure 5 compares equity behavior of such a combined system with its separate components. An additional and most important value of the final step is also visible while investigating drawdown fluctuations over the entire analyzed period (please see Figure 6).

The fluctuations of drawdown on Figure 6 present significant decrease of maximum and average drawdown for the combination of our three systems (I+II+III_system) in comparison to single systems. What is more important, the same can be seen for other risk statistics (*aSD, MLD*) for the in-sample period (Table 7 in the last column), and this phenomenon is observed with unchanged profitability statistics and highly increased statistics presenting the joint picture of risk and returns.

The extent of generated additional value from this combination one may precisely assess by comparing performance statistics presented in Table 7. To avoid bias of in-sample effect, statistics were calculated for out-of-sample data. The results are in line with expectations. Significantly lower risk was produced by the final system

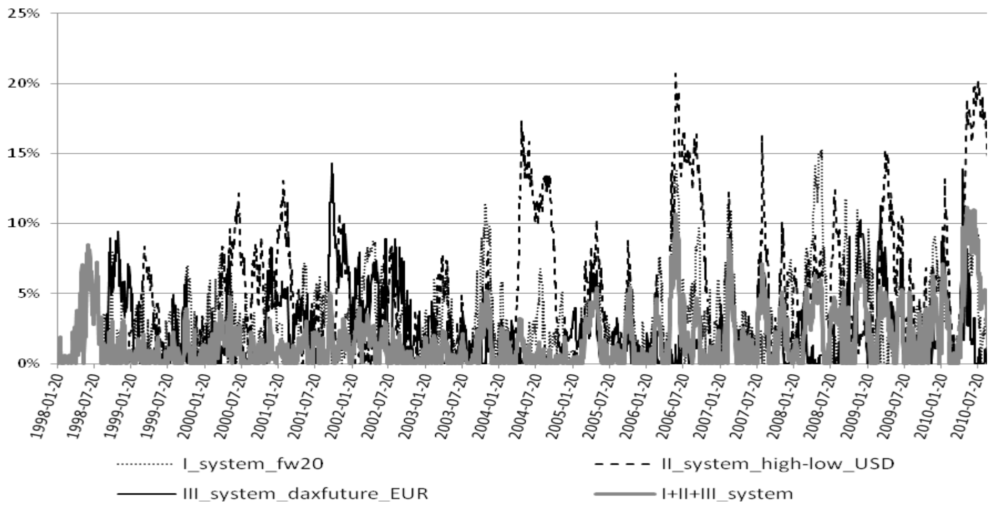
5 The correlation coefficients between our three systems were close to 0.

Figure 5: Equity lines for systems I, II, III and combination of these three systems



* Figure 5 presents equity lines (assuming the initial investment of 1 million) for I_system-fw20, II_system_high-low and III_system_daxfuture in comparison to I+II+III_system in the period: 1998.01.20-2010.12.31. We use logarithmic scale.

Figure 6: Drawdown for I, II, III systems and the combination of these three systems



* Figure 6 presents the fluctuations of drawdown for I_system-fw20, II_system_high-low and III¬_system_daxfuture in comparison to I+II+III_system in the period: 1998.01.20-2010.12.31.

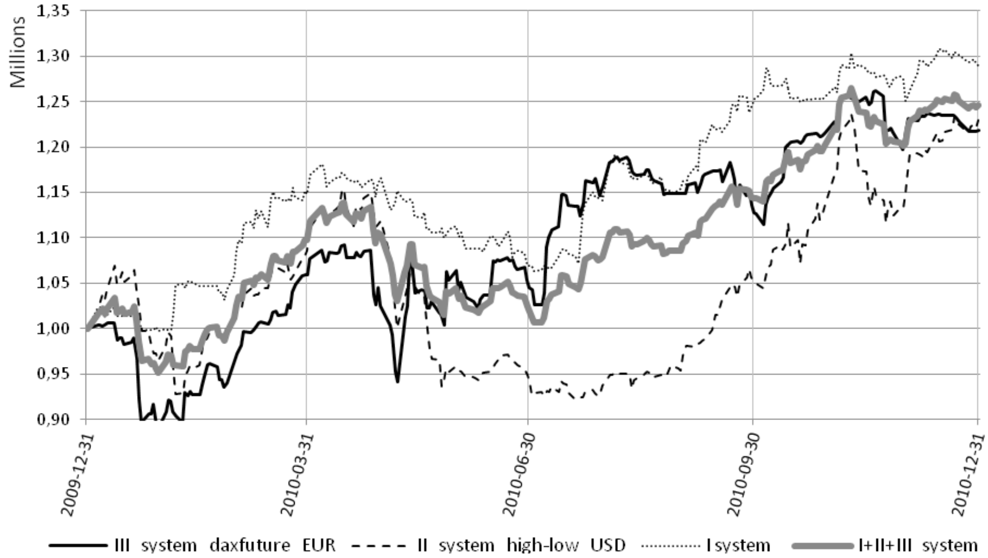
simultaneously keeping a stable level of returns. *Annual standard deviation* decreased to 13.6% while for separate components it reaches 14.0%, 18.0% and 21.3% for I, II and III system respectively. The fluctuations of equity lines for out-of-sample period are presented on Figure 7. This figure once again confirms the stabilizing effect of the combination of n different systems on the level of overall risk. What is more important, these results show that that the process of adding new components to the final system could be infinite.

Table 7: Performance statistics for system I, II, III and combination of these three systems (out-of-sample period)

Statistic name	Abbre-viation of statistics	I system _fw20	II_system _high--low_USD	III_system _daxfuture _EUR	I+II+III system out-of--sample	I+II+III system in--sample
annual return compounded	ARC	29,0%	23,0%	21,8%	24,6%	35,5%
annualstdev	aSD	14,0%	18,0%	21,3%	13,6%	12,3%
information ratio	IR	2,08	1,27	1,02	1,81	2,88
maximum drawdown	MD	9,9%	20,1%	13,9%	11,6%	11,2%
max financial leverage	maxFL	73%	45%	30%		50%
maximum loss duration (in years)	MLD	0,32	0,55	0,24	0,42	0,42
Sharpe ratio	Sharpe	1,7	1,1	0,8	1,4	2,5
annual return compounded (%) / max drawdown (%)	ARC / MD	2,9	1,1	1,6	2,1	3,2
average per year max drawdown (%)	AMD	9,9%	20,1%	7,4%	11,6%	6,4%
annual return compounded (%) / average per year max drawdown (%)	ARC / AMD	2,9	1,1	3,0	2,1	5,5
allrisk	allrisk	0,44	3,99	0,53	0,78	0,37

* Table 7 presents detailed statistics for I_system-fw20, II_system_high-low and III_system_daxfuture in comparison to I+II+III_system in out-of-sample period.

Figure 7: Equity lines for systems I, II, III and the combination of these three systems (out-of-sample period)



* Figure 7 presents equity lines (assuming the initial investment of 1 million) for I_system-fw20, II_system_high-low and III_system_daxfuture in comparison to I+II+III_system in out-of-sample period.

Conclusions

This study confirms that we are able to beat the market in a consecutive manner. This positively verifies our main hypothesis defined at the beginning. Hence, we can say that **we can create investment systems beating the market in a consecutive manner independent of cyclically occurring market turmoil.** The key driver of the success is a multi-stage technique which enables us to obtain results that are much closer to the ones from the in-sample period and consequently much higher comparing to alternative investments practically in each context: profit, risk and measures connecting risk and profit. I, II and III systems earned approximately 35% annually in comparison to 10% annually on average for the best alternative investments. At the same time, our ATS is characterized by several times lower risk statistics. This enables us to obtain an *information ratio* close to 2 (in-sample-period) and above 1 for out-of-sample period.

Moreover, the applied techniques allow us to reach risk statistics for the tested ATS even lower than for a potentially "risk-free investment", e.g. pension funds, while their rates of return were several times higher than this potentially "risk free" alternative.

Applying the developed techniques for non-optimized ATS (II_system) provided us with the similar results. This proves that the key driver of the system efficiency is not the optimization process. A major role is played by the whole process of the construction especially cash management rules, selection of various financial instruments and various strategies, reoptimization, rebalancing and reconstruction of the system when new financial data come in.

These ATS operate on several markets which on the one hand prove that developed techniques are scalable and applicable for several financial instruments. On the other hand, a multi-market approach allows minimizing the liquidity risk and overall risk. A new approach used in allocation setting the transactional unit for each system is one of the most important factors for system performance (cash management system). It has to be considered in conjunction with risk management methodology. The next important factor are the strategy evaluation criteria (the boundary conditions) used during the testing phase, which enable us to find the best final version of the system. Additionally, focusing on risk statistics in the in-sample period increases the probability that similar results will persist in the out-of-sample period.

Finally, the crucial elements of the ATS construction process are reoptimization, rebalancing and reconstruction of the system after the testing period. Having already all the mentioned elements in place significantly increases the probability of reaching the defined results for the system.

Last but not least, results presented for I+II+II_ system enable us to conclude that there is no final point in the ATS construction process. Assuming that we can find additional systems characterized by very low correlation coefficients we should continue the process of adding them to our complex system (I+II+II+…_system). This means that there is still a huge space for further research.

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