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Downtrend Algorithm and Hedging Strategy in Futures Market

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***Abstract*—**The paper investigates downtrend algorithm and trading strategy based on chart pattern recognition and technical analysis in futures market. The proposed chart formation is a pattern with the lowest low in the middle and one higher low on each side. The contribution of this paper lies in the reinforcement of statements about the profitability of momentum trend trading strategies. Practical benefit of the research is a trading algorithm in falling markets and back-test analysis in futures markets. When based on daily data, the algorithm has generated positive results, especially when the market had downtrend period. Downtrend algorithm can be applied as a hedge strategy against possible sudden market crashes. The proposed strategy can be interesting for futures traders, hedge funds or scientific researchers performing technical or algorithmic market analysis based on momentum trend trading.

***Keywords*—**trading algorithm, chart pattern, downtrend trading, futures market, hedging

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I. Introduction

A set of regulatory change, like electronic order handling rules of 1997, put the foundation for a change of order handling rules in financial markets.

Traditional floor based exchange model characterized by open-outcry has been replaced by electronic exchanges altogether with electronic communication networks (ECN). The shift set an expansion of technical market analysis, algorithmic trading, and high frequency trading techniques. This shift and expansion of trading instruments, automatic trading and computational analysis has also attracted attention of many academics and scientific researchers. The change triggered a birth of academic curriculums like financial engineering, quantitative analysis or financial informatics. Expansion of time series and quantitative analysis altogether with a growing demand for trading algorithms has shown an increasing belief that computation techniques can be helpful for decision-making in financial markets [1-2-3].

Most of scientific papers studying technical market analysis and trend trading are concentrating on equity or currency markets [4-5-6]. However recent expansion of derivative instruments altogether with continuing economic uncertainty after the market crash in 2008 leads to a growing demand for hedging businesses. Therefore trading volumes from equity and currency markets increasingly move to futures and options markets [7].

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The need for computational analysis in futures markets is in a great demand.

In trading industry there are several basic directions of financial markets analysis. The first one is fundamental, trying to forecast market movements evaluating financial statements or economical and statistical data. Another one is technical analysis, based on the belief that all financial or economic factors are already reflected in price changes of financial instrument and so the price change and trend analysis are essential [8].

Since fundamental analysis concentrate on long term investments, like quarterly or yearly data, trying to make decisions on value of the market, rather than emotions or short runs of technical overtrading, technical analysis concentrates on short term investments focusing on momentum trading and finding precise levels of entering and exiting the market [9]. Recent frauds in economic and financial statements, expansion of automated electronic trading [10] altogether with a decrease of the average holding period of investments [11] leads to a choice of technical analysis as a primary instrument for building trading algorithms. Despite the lack of information about profitable algorithms some research papers claim that the application of momentum trend trading and chart patterns can give useful information and be profitable to market participants [12-13-14]. Trend following is the trading philosophy by which buying/selling decisions are made solely according to the observed market trend [4]. Joelle Miffre and Georgios Rallis state that while contrarian strategies do not work, some profitable momentum strategies generate 9.38% average return a year [12]. Similar positive results with only monthly dataset are presented in the paper by the researches from University of Richmond, Alabama A&M University and Southern Illinois University [13].

Peter Gomber, professor at Goethe University, Germany has also done a research about high frequency trading strategies and has concluded that *short term momentum* strategies usually trade aggressively (taking liquidity) and aim at earning profits from market *movements/trends* [15]. Dr. Galen Burghardt, adjunct professor at the University of Chicago's School of business, also affirms that among commodity trading advisors[2] (CTA) *trend following* is most commonly associated as the predominant strategy of technical analysis [16]. According to *PerTrac Financial Solutions*[3] active CTAs have historically provided better inflation hedging properties than an investment in indexed long–only commodities and it is mainly because of the ability to profit in both rising and falling markets, while investment in long only index produces positive returns only when market is rising.

[2] A Commodity trading advisor (CTA) is a financial professional licensed and regulated by National Futures Association and is a trained expert who is employed by a fund or individual clients to invest capital by engaging the commodities spot, physical, and futures markets.

[3] PerTrac provides sophisticated analytics, reporting and communications software and services for investment professionals, including pensions, family offices, hedge funds, long-only managers, endowments, sovereign wealth funds, funds of funds and industry service providers.

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Similar positive approaches toward trend trading can be also found in conversations with practitioners and America's top traders [17].

Considering a short review of the previous researches the main purpose of this paper is to find an algorithm related to trend trading approach, to back-test it, and to reinforce statements about hedging opportunities with momentum downtrend trading when markets fall. For that purpose futures are the most suitable, since short-selling restrictions are often imposed in stock markets, while taking short positions in futures market is as easy as taking long positions. We hope that this research might be interesting to futures market traders, companies implementing hedge strategies in their businesses and also researchers performing technical or algorithmic analysis based on momentum trend trading and interested in potential of falling markets.

The paper is organized as follows: Section 2 provides the basic concept of the proposed downtrend algorithm. Section 3 explains the details of experimental investigations. Experimental results are evaluated in section 4 and the main conclusions of the research are presented in Section 5.

II. Basic Concept of the Proposed Downtrend Algorithm

The proposed downtrend algorithm is based on downtrend following system and continuous chart pattern. Chart pattern can be defined as an indicator of technical analysis mostly applied for short term trading and evaluation of open/close prices of the position.

There are two types of patterns in technical analysis, reversal and continuation [19]. A reversal pattern signals that a prior trend will reverse upon completion of the pattern. A continuation pattern signals that a trend will continue once the pattern is triggered [18]. A continuation pattern is mostly used when the market is overreacted and causes movement trends to last longer than anticipated.

The proposed downtrend algorithm is based on fractal pattern and chaos theory, presented by Benoit B. Mandelbrot [20,21] and developed as a trading tool by Ph.D. Bill M.Williams [22, 23]. The fractal formation is constructed from bar charts[4] and applied for evaluating the possibility of further continuous movement in the market. Fig.1 shows several different varieties of down fractal formations developed by B.M.Williams [23]:



Fig. 1 Down- fractal (Short sell) examples

[4] Bar chart is a type of chart typically used to illustrate price movements of a financial instrument over time. It also can be named as OHLC chart (Open-High-Low-Close).

A fractal definition by B.M.Williams is as follows:

"A Fractal must have two preceding and two following bars with lower highs (higher lows in a down move). In a buy Fractal, we are interested only in the bars' high. In a sell Fractal, we are interests only in the bars' low." [22]. Fig.2 shows real market example of down fractals to make it easier to understand:

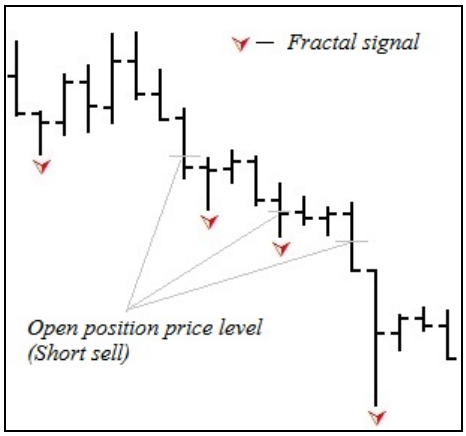


Fig. 2 Down- fractal (Short sell) market examples

Fig. 1 shows that a variety of fractal patterns can be unlimited as long as there are two preceding and two following chart bars with higher lows altogether with equal bars in between. The time horizon for a fractal to make a formation is unlimited. Fig. 2 shows fractal signals generated by real market (Eur/USD 30 min bar chart was taken as an example). Gray horizontal lines point price levels for short sell market entries.

A. Weaknesses of a typical fractal

Examples in Fig.1 and Fig.2 show the variety of possible shapes of fractal formation. The variety makes a formation subjective and not precise enough, especially when trying to rank and compare the signals generated by different futures. A lack of signal quality measurement makes a signal inaccurate especially when trying to apply B.M.Williams strategy in real trading or processing back-test analysis. A typical fractal formation also does not show precise level for exiting the market. A stop order or market exit point is determined not by formation itself but by other indicators of technical analysis, e.g. moving averages. These inaccuracies and overall complexity of the strategy considering all indicators necessary for Williams approach, like Alligator, Awesome oscillator, Accelerator oscillator, MFI index, Elliot Waves [23] make it nearly impossible to determine the strategy and put it on algorithm.

In general, typical fractals were found rather subjective and therefore often being presented in conjunction with other forms of technical analysis, like moving averages, Elliott Waves analysis, MACD indicator and etc. It makes a typical fractal formation to be a good decision support tool, but not the basic indicator itself. Therefore, a decision to search for a novel, more accurate, determined and, at the same time, still conformable with trend trading and chaos theory chart pattern has been made.

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B. Modified downtrend fractal formation

Modified downtrend fractal formation is composed of 3 consecutive chart bars. A fractal occurs when there is a pattern with the lowest low in the middle and one higher low on each side, as it can be seen in formation example in Fig. 3.

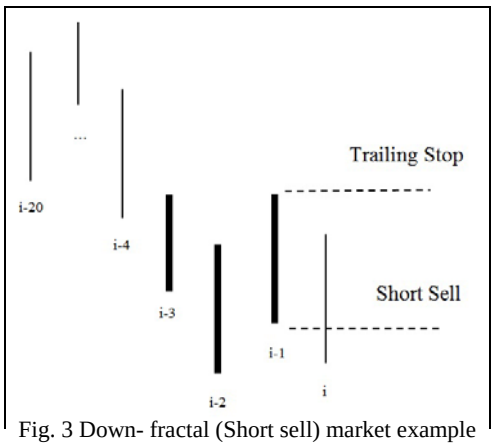


Fig. 3 Down- fractal (Short sell) market example

An algorithm opens a short position when the current price (i) hits the second bar's (i-1) lowest price. An opening price is set at the level of the second bar's (i-1) lowest price minus a tick size (smallest price increment for a contract). Each contract has a different tick size because of the contract size. Tick size can have a decimal or fractional number format. Most of the time decimal number format is used because of standardization of data sets, e.g. CSI data format). If there is a sudden drop in the market and current open price of (i) bar opens lower than the lowest price of (i-1) period a gap[5] is formed and a short sell signal is identified as an opening price.

Evaluating precise time for exiting the market is just as important as determining the best time to enter it. Algorithm based on truncated down fractal formation suggests placing a trailing stop order at the level of the second bars *i-1* highest price plus a tick size. Trailing stop order ensures that stop price is adjusted and moved to the next bar highest price each time the new bar is formed. Trailing stop lets profits run and cut losses if a sudden market downtrend changes. If the price is falling, the trailing stop level lowers as well. And if a price movement reverses trailing stop closes the position. If there is a sudden jump in the market and following bar opens with a gap up, cover short price is set as an open price of this following bar. Entering and exiting the market cannot be done during the time frame of the same bar.

C. Signal quality

Most of technical analysis indicators cannot be qualitatively back-tested because of the absence of signal quality evaluation. The same problem faces typical fractal where there is no formula for signal strength measurement. In order to avoid inaccuracies often back-test analysis is done with only historical data from the preselected particular contract.

[5] Gap- break between prices on a chart that occurs when the price of financial instrument makes a sharp move up or down with no trades occurring in between

No portfolio diversification or ranking processes are being encountered. Such analysis can be applied but it is static, subjective and lacks flexibility to all the time changing instruments, e.g. trading activity moves to other markets, and market behavior (trendy market is changed by consolidated, reversal, choppy and etc.). Doing such simplified back test the results are unreliable because of taking only a particular contract or the most suitable time period for analysis. In order to avoid such subjectivity ranking techniques of contracts and the quality of signals must be considered [9].

The proposed downtrend algorithm based on truncated fractal formation searches for futures contracts that during the period of two days had decreased in a price the most. The quality of the contract and its rank for the trade is measured using the following percentage equation:

$$R = \left[\frac{C(i-2)*100}{C(i-4)} - 100 \right] \quad (1)$$

In the equation (1) *R* represents the rank of a particular contract and *C*- the closing price of the periods *i-2* and *i-4*. The biggest decrease in a price of a particular contract during the period between *i-4* and *i-2* also means the strongest signal and the highest rank. If chart pattern is formed with several contracts at the time, the one with the highest rank is chosen for a trade. Truncated formation when using only three periods for pattern formation and additional two bars for signal strength evaluation increases prediction sharpness because of only the latest data used for decision making.

III. Experimental Setup

The efficiency of downtrend algorithm and hedging strategy against down crash of the markets was back-tested with historical data collected from the biggest US and EU futures exchanges. The daily time series were collected from exchanges like GLOBEX, ECBOT, CFE, NYMEX, ICE and ICE-NYBOT from 2008 till 2011.11. CSI UA software developed by CSI Commodity Systems Inc. was chosen as the primary instrument when collecting combined floor and electronic data.

The most active and liquid contracts from each sector of futures market were included in experimental research. The following sectors were encountered: Energies, Metals, Grains, Financials, Equity Indices, Currencies, Softs and Meats. These are the main sectors of futures market [24]. The following table presents contracts included in the research:

TABLE I
Futures Contracts

Contract name	Tick size	Full Point value	OIMR	Commissions
WTI Crude Oil	0.01	1000	8775	$2.32
Henry Hub Natural Gas	0.001	10000	3713	$2.32
Heating Oil #2	0.0001	42000	9534	$2.32
Gold	0.1	100	6075	$2.32
Silver	0.1	50	25920	$2.32
Copper	0.05	250	5852	$2.32

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Platinum	0.1	50	4375	$2.32
Corn	0.25	50	3260	$2.68
Soybean	0.25	50	4388	$2.68
Wheat	0.25	50	4374	$2.68
Soybean oil	0.01	600	1688	$2.68
Soybean meal	0.1	100	2363	$2.68
Eurodollar	0.0025	2500	608	$2.06
10 Year Treasury Note	0.015625	1000	2049	$1.43
30 Year Treasury Note	0.015625	1000	3078	$1.43
2 Year Treasury Note	0.0078125	2000	675	$1.43
E-mini S&P500	0.25	50	5000	$2.01
E-mini Nasdaq 100	0.25	20	3500	$2.01
DJIA Index Mini	1	5	5000	$2.01
Russell 2000 mini	0.05	100	4375	$2.01
Volatility Index	0.05	1000	4000	$1.87
Euro FX	0.0001	125000	5616	$2.47
Japanese Yen	0.0001	125000	3375	$2.47
British Pound	0.0001	62500	2147	$2.47
Australian Dollar	0.0001	100000	3213	$2.47
Canadian dollar	0.0001	100000	2484	$2.47
Sugar #11	0.01	1120	3557	$2.62
Cotton #2	0.01	500	8400	$2.62
Orange Juice	0.05	150	1798	$2.62
Coffee	0.05	375	7787	$2.62
Lumber	0.1	110	2745	$2,76
Live Cattle	0.025	400	2106	$2.76
Lean Hogs	0.025	400	2160	$2.76
Feeder Cattle	0.025	500	3119	$2.76
Class III Milk	0.01	2000	675	$2,76

Contracts in Table I were chosen involving a broad range of sectors and considering trade rates and volumes of particular contracts. Trade rates and volumes were taken from 2010 annual survey [7], CRB statistics (Commodity Research Bureau) and Barchart.com, Inc on-line data. In general we can say that contracts presented in Table 1 are the most liquid in their group and altogether take the biggest part of trading activity in the North American futures markets. Therefore they can be taken as a benchmark and applied in back-testing the strategies.

Table I also shows specifications of the contracts necessary for calculating risk, profitability and position size when back-testing trading strategies. 'Full point value' and Overnight Initial margin requirements (OIMR) are necessary for position size calculations. Full Point Value is derived by exchanges taking into consideration total value of the contract. OIMR is also calculated by exchanges and depends on market volatility. Variables are expressed in the currency of traded product and mostly based on SPAN margin algorithm. The SPAN margin algorithm defines a standard set of market outcome scenarios with a one day time horizon. In our research OIMR values are taken from Interactive Brokers LLC data base and can be understood as a margin deposit for end of day trading. Tick size presented in Table 1 is necessary defining precise prices for opening and closing positions. Currency and commissions show the costs of making a trade with different contracts. Commission charges have a fixed rate per contract and include all the fees from exchanges and regulatory institutions. The charges are based on Interactive Brokers LLC commission table structure.

A. Continuous futures data series

Historical data series of futures market faces problems because of short-lived contracts. Futures are short-lived contracts that are only active for a few months. The gaps between the prices of different contracts must be removed when implementing long term (over one year) back test analysis. There are several methods to generate continuous futures data series, like Forward adjusted; proportionally adjusted; Gann series; perpetual series or backward adjusted series [25]. Taking into account the strengths and weaknesses of different methods backward adjusted (BA) data series were taken when doing long term analysis. BA method uses the actual prices of the current contract with a backward correction of price discontinuities for earlier delivery months. This adjustment requires applying recalculation of the earlier contract prices with respect to the price of the current (or later) contract [26]. The problem with negative prices was resolved by adding a fixed amount of points to make non-negative values. This fix was necessary only with historical data of Soybean meal contract. A roll over timing was based on open interest and volume of the contracts. This timing ensures the most liquid trading days for contracts change and the lowest risk of execution slippage. Confirmation signal or roll on a second consecutive trigger was applied in order to avoid false signals generated by a sudden temporary change in volume or open interest.

B. Calculation of returns and position size

Futures are traded with margin. Margin can be treated as a little part of a full contract value. For example, with a margin of 10% around 10 contracts can be acquired by paying no more than a full value of one contract.

This gives a leverage that makes trading futures more risky and also profitable. The easiest calculation can be made with a contract where the full point value equals to 1. Then each $1 change in contract price represents $1 profit/loss per contract. Different contracts have different full point values, see Table 1.

If, for example, point value is 20, as trading with E-mini Nasdaq 100, each point change in value of the contract generates profit/loss of $20. Profitability of investment is calculated multiplying the number of contracts by full point value and by change in value of the contract. The following equation presents profit/loss calculations in futures markets considering commission charges and interest on margin paid:

$$P/L = N \times ((P_C - P_O) \times FPV_i - 2 \times Comm) - Int \quad (2)$$

Eq. 2 presents closing and opening prices (P_c; P_o) of a particular contract. FPV shows *Full Point value* of the contract *i* (see: Table 1). Variable *Comm* is necessary for evaluation of commissions per trade. *Comm* is multiplied by 2 because of opening and closing transactions. The *N* variable represents the number of contracts and *Int* shows interest paid on margin.

Commodity trading advisors recommend to risk as little of total equity as possible per trade. It is common in industry that larger capitalized traders risk rarely more than 1% per trade.

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Smaller size traders, e.g. with an account smaller than 250k tend to risk no more than 2 - 5% of their total equity per trade [17]. Margin setting and risk ratio are used to determine a number of contracts to be acquired. Let's take an example: initial equity is set to $200'000; investor wants to risk no more than 5% of equity per single trade and the margin deposit (OIMR, see Table 1) is $5'000 (as with E-mini S&P500 at 25/07/11). In such case an appropriate position size should be $200'000 * 5% = $10'000. That means that trading E-mini S&P500 contract with such an amount of money no more than 2 contracts per single trade can be purchased ($10'000/$5'000 = 2). There is an equation for evaluation of size of a single trade:

$$PS = \frac{Ie \times \frac{Rr}{100} - 2 \times Comm}{OIMR_i} \quad (3)$$

Eq. (3) presents calculation of position size (*PS*). Variable *Ie* shows the size of initial capital and *Rr* (Risk ratio)-percentage size of risk taken if compared to total equity. *Rr* depends on the size of initial equity and also on the forwardness toward risk taking. For example if a trader can afford to risk a third of total equity per single trade the *Rr* coefficient equals to about 33. The variable *Comm* shows the size of commissions per trade and can be even excluded if the size of position is rather a small one and the impact of commissions is not significant. As stated earlier *OIMR* is Overnight Initial Margin Requirements for opening position with a particular contract *i*. *OIMR* values (Table 1) can change if market volatility changes.

IV. Experimental Results

The downtrend algorithm was back tested and computations were carried out with Matlab software of technical computing.The detailed functioning of back tested algorithm can be described as follows:

- Continuous futures data series were generated (Backward adjusted method)
- Ranking algorithm (Eq.1) was applied and 7 different futures with the best ranks and truncated fractal formation formed were sold short (Fig.3). Position size was calculated according to (Eq.3), where *Rr* coefficient equals to 4.5%.
- Open positions were covered after trailing stop price was triggered (Fig.3)
- Total return on trading was estimated every day (Eq.2)

Experimental results of the algorithm are shown in the following figure:

Figure 4 shows that downtrend algorithm had outperformed the benchmark CRB index (Commodity Research Bureau index) and the total return at the end of testing period was nearly 70%. Fig.4. also proves that the best results were received when a sharp decline in the market was present, e.g. during the 2008 market crash. Trading algorithm was not performing as well as during the market crash and managed only to keep profits steady during up-trend move. Results confirm a capability of downtrend algorithm in falling markets.

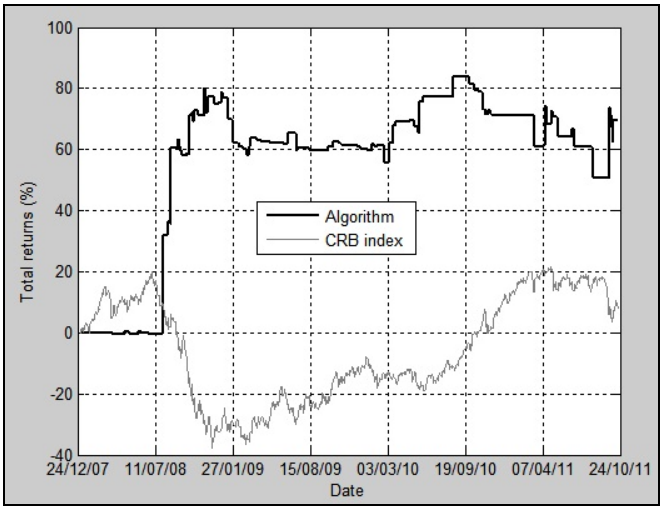


Fig. 4 Total returns using downtrend algorithm

V. Conclusions and Discussion

The downtrend algorithm based on short term bar chart formation was presented in the paper. Contracts specifics like full point value and overnight initial margin requirement necessary for computational analysis were discussed in the paper. Equations related to profitability and position size were also presented. Experimental research was carried out on a daily historical data. The most active futures contracts from different sectors were chosen for analysis. Combined floor and electronic daily data was downloaded from GLOBEX, ECBOT, CFE, NYMEX, ICE and ICE-NYBOT exchanges. The research of the algorithm has proved profitability in falling markets and stability in up-trend movement. Considering recent economic uncertainties and possible downtrend moves the strategy can be applied as a hedging instrument against possible increase in risk associated with market crashes. The downtrend algorithm gives some promising results and can be attractive for hedge funds when managing the risks associated with price fluctuations or futures market participants who intend trading short term strategies, especially when volatility in markets increases. Despite good preliminary results more extensive researches with algorithm should be done (e.g. combine up and down trend trading) to evaluate more precisely the whole domain of the possible applications of this strategy.

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