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Inside this Issue

”I don’t believe in psychology.
I believe in good moves.”
—Bobby Fischer
11th World Chess Champion

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IFTA Journal

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Letter From the Editor

By Dr. Rolf Wetzer, CFTe, MFTA

Dear IFTA Colleagues and Friends:

When Aurélia Gerber left as *Journal* chair within the IFTA board, I wondered, "who's going to fill her shoes?" She edited the *Journal* for the last six years, and we are very proud of every single issue that she produced. Then, Mohamed called and asked me to help out with the *Journal*—and I instantly knew that the bar probably was raised too high. Therefore, the first thing I want to do is to thank Aurélia for the awesome work she has done for IFTA.

Autumn is IFTA's high season. We have the Annual General Meeting, the Annual Conference, and publication of the *Journal*. This year's conference will be in Egypt, hosted by ESTA. It will be the 32nd edition of the conference, and the theme will be "History Speaks". I still recall the 2008 conference in Sharm el Sheikh. That was our 20th conference and first one held in that region of the world. It felt good to go to Egypt at that time, and I am looking forward to returning to Cairo in October.

This year's *Journal* will be packed with a lot of papers coming from different sources. For the first time we will have an epitaph for a fellow technician from Australia. This is our contribution to "History Speaks".

The first two papers are from our MFTA program. One paper is about technical sector rotation, and the other one presents an original cycle technique. If you are interested in writing an MFTA thesis yourself, please register for the program via our website: www.ifta.org.

I am very proud that we have a very good and stable relationship with the National Association of Active Investment Managers (NAAIM). For several years in a row, NAAIM has allowed us to publish their Wagner/Founders award paper. This year, the winner is a colleague who is also a member of our Italian society SIAT. I would like to mention that NAAIM welcomes non-NAAIM members to visit its homepage at www.naaim.org, where you will find many other valuable papers.

We have two papers from colleagues who participated in VTAD's award. I especially would like to thank both authors, who not only dared to publish their work with us, but also took the effort to translate and edit their work from German into English.

Traditionally, the greatest resources for the *Journal* are our colleagues from all over the world. They contributed four articles. We feel very honored that we can present an article written by Thomas Bulkowski. Thomas is one of the world's leading authorities in graphical pattern recognition.

...the greatest resources for the Journal are our colleagues from all over the world.

As usual, the *Journal* will close with a book review written by Regina Meani, one of our long-time *IFTA Journal* editors and writers. She has been working for the *Journal* since 2007. Thank you very much for all the time and volunteer work that you donated to IFTA over all the years.

Last, but not least, we would like to thank the production team at Management Solutions Plus, and in particular, Linda Bernetich, Lynne Agoston, and Jennifer Olivares for their administrative, technical editing, and publishing work.

I hope to see you all in Cairo!
Best regards,
Dr. Rolf Wetzer, CFTe, MFTA

An Investment Strategy to Beat the U.S. Stock Market for Investors and Professionals

By Alessandro Moretti, CFTe, MFTA

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Abstract

The U.S. stock market is one of the most difficult for professional fund managers to beat. Statistics say that more than 97% of actively managed funds have failed to do better than the U.S. stock market in the last 10 years. Those are really amazing numbers. Private investors are not doing any better. They can try to beat the market by relying on professional managers, knowing that they will most likely do worse. Or they can give up trying to do it themselves but even in this case most of them have neither the skills nor the means to do it. Moreover, they also have to deal with their own emotionality, which pushes them to liquidate their investments during the strong downturns typical of the stock markets. In short, it is a very difficult situation for both managers and investors. In this paper, I will present an operational strategy which, through technical analysis, relative strength, sector rotation, and capital management, enables us to invest and achieve the objective of beating the American stock market in the long term. The presented strategy has the great advantage of being able to be implemented by both small private investors and large managers, via financial advisors.

Introduction

Identification of the Trouble

An investor who today wants to start investing his savings in the stock market has two options:

- The first is to rely on active management. In this case, there are professional managers who invest the capital of their clients with the aim of doing better than a specific reference market called "Benchmark"; "Doing better" is understood as achieving higher performance with the same or even lower risk. In this case, the investor wants to try to beat the market but takes the risk of being able to do worse.
- The second option is to rely on passive management. In this case, there are funds that invest investors' capital by passively replicating the trend of a declared benchmark. The goal is not to do better than the benchmark but simply
- to do the same as the benchmark. Therefore, have as close a return as possible on the same volatility. In this case, the possibility of doing better than the market is waived, but the risk of doing worse is avoided.

Let's focus on active management right now.

Table 1 represents research conducted by Morningstar. The table shows the percentage of actively managed funds that have been beaten by their respective benchmarks in different timeframes ranging from one year up to 10 years.

Table 1. Actively Managed Funds That Beat the Benchmark

Report 1: Percentage of European Equity Funds Outperformed by Benchmarks

FUND CATEGORY	COMPARISON INDEX	ONE-YEAR	THREE-YEAR	FIVE-YEAR	TEN-YEAR
EURO-DENOMINATED FUNDS (EUR)					
Europe Equity	S&P Europe 350	46.59	59.21	73.26	85.44
Eurozone Equity	S&P Eurozone BMI	73.70	77.41	87.54	88.01
Nordic Equity	S&P Nordic BMI	73.17	50.00	63.16	65.71
Global Equity	S&P Global 1200	53.76	91.37	94.46	98.85
Emerging Markets Equity	S&P/IFCI	71.61	92.41	91.75	97.35
U.S. Equity	S&P 500	71.24	89.78	95.88	97.80
France Equity	S&P France BMI	52.91	58.67	70.12	81.85
Germany Equity	S&P Germany BMI	39.33	61.05	71.58	75.42
Italy Equity	S&P Italy BMI	28.30	39.58	42.31	71.43
Spain Equity	S&P Spain BMI	68.24	53.85	71.60	79.20
Netherlands Equity	S&P Netherlands BMI	75.00	77.78	92.86	93.94
POUND STERLING-DENOMINATED FUNDS (GBP)					
Europe Equity	S&P Europe 350	38.89	45.83	59.57	75.82
Europe Ex-UK Equity	S&P Europe Ex-UK BMI	56.15	69.11	74.80	73.51
UK Equity	S&P United Kingdom BMI	46.40	59.61	54.14	75.19
UK Large-/Mid-Cap Equity	S&P United Kingdom LargeMidCap	54.10	64.71	47.66	73.35
UK Small-Cap Equity	S&P United Kingdom SmallCap	19.70	41.10	56.58	72.84
Global Equity	S&P Global 1200	52.72	82.35	86.24	94.89
Emerging Markets Equity	S&P/IFCI	62.43	80.98	79.53	84.85
U.S. Equity	S&P 500	67.11	88.37	92.94	93.41
FUNDS DENOMINATED IN OTHER EUROPEAN LOCAL CURRENCIES					
Denmark Equity	S&P Denmark BMI	100.00	24.24	29.41	82.86
Poland Equity	S&P Poland BMI	93.48	76.60	65.31	94.29
Switzerland Equity	S&P Switzerland BMI	37.99	33.52	53.07	72.78
Sweden Equity	S&P Sweden BMI	49.11	45.54	53.72	75.59

Source: S&P Dow Jones Indices LLC, Morningstar. Data for periods ending Dec. 29, 2017. Outperformance is based on equal-weighted fund counts. Index performance based on total return. Past performance is no guarantee of future results. Table is provided for illustrative purposes.

Let's go to the last column on the right—the one that shows the measured data over a 10-year time horizon. The results are terrible.

If we take the American stock market, 97.8% of all active funds have done worse than the benchmark. On the global stock market, this does not change. In this case, the number rises to 98.85%. Practically only about two out of every 100 funds available has managed to do better than the market, which is to achieve the purpose for which they exist. The column with the longest time horizon has been taken for analysis because this eliminates the fortune/bad luck effect and because when you invest in the stock market, you do so with a long-term objective.

Having said that, it is clear what the problem is:

- Investors side: To date, those who want to try to invest with the aim of doing better than the market do not have valid tools to try. The majority of those who tried to do this 10 years ago by relying on active funds find themselves with the opposite result. The numbers are striking and play against active management. Those who have tried to do it by themselves have realised that they have neither the skills nor the means to do it.
- Managers side: Due to the high management fees and the

strong competition on the markets, they are unable to produce value for their customers. In fact, they destroy it.

There is also another problem related to behavioural finance. One of the most important criticalities that has been found with investors is the one related to the handling of emotions. It is true, in fact, that the stock market offers great returns in the long term, but it is also true that in the short term, it can produce significant losses.

It is not uncommon to see a stock market losing more than 50% of its value in a few months as a result of a depressive phase of the economy. However, the investor, in the vast majority of cases, cannot tolerate such losses and often finds himself selling and exiting the market at the very worst times.

Identification of the Aim

Once the two real problems are highlighted, it becomes pretty easy to identify the objectives:

- Finding an active management approach that allows you to create value for your own capital and your customers. In other words, to find a strategy that, once the benchmark to be beaten has been identified, actually allows higher yields to be achieved for the same risk in the long term—doing what 98% of the already existing active funds failed to do in the last 10 years.
- Finding an approach to contain losses during negative market phases in order to reduce the negative effects of behavioral finance and investors' emotional decisions.

Realization of the Strategy

To implement the strategy that is the subject of this research, I have started from the identification of the target user. The first question I asked myself was: who is this strategy aimed at?

The answer to this question is very simple. There are four target users of this strategy:

- Private investors who want to invest their own capital.
- Financial advisors who want to manage their clients' capital more actively and efficiently.
- Active fund managers who want to have a mechanical approach to beat the benchmark.
- Passive funds that want to make more efficient products based on mechanical strategies.

As you can see, the objective of the research was very ambitious right from the start. In fact, these four possible end-users have different skills, different capital, and different instrumentation. A private investor has lower capital and less expertise and complex equipment than, for example, an active fund manager.

To make a "dress" that would suit all these subjects, I had to focus on simplicity—just the simplicity that has characterized my operations in the financial markets in over

10 years of experience. I am a strong supporter of the "KISS" approach, "Keep it Simple, Stupid".

It is from this need, therefore, that the idea of implementing a strategy that is simple to apply was born.

In fact, a simple system can be used indiscriminately by investors with fewer skills and tools and by professional managers. A complex system, on the other hand, could have been used by professional managers but would have cut off consultants and private investors.

In addition, a system with simple operation is also more controllable than a complex system. Monitoring and optimizing a system composed of two variables is undoubtedly easier than monitoring a system composed of 20 variables. Plus, note that simpler does not mean more trivial and less professional.

To do this, I have therefore started from the following points:

- Few indicators to make the system easily replicable and, above all, controllable.
- Few rules to avoid unnecessary complexities that often generate inefficiencies.
- Weekly operation to be followed, even by those who cannot stay every day on the markets.
- Few operations that last longer to reduce the commission impact of buying and selling operations.
- Mechanisation to be able to check if the current results are in line with those of the past and to be able to also put it into practice with software.
- Replicable with financial instruments accessible not only to professional managers and not only to investors with high capital.

Then, I looked for a methodology that would have helped to contain losses in the negative phases of the markets.

As a reference market to beat, I gave myself precisely that American stock market that 98% of the funds failed to beat. Specifically, I used the Dow Jones US Total Market.

The Fundamental Idea

The first concept from which I started is the following:

If I want to beat the American stock market and if I want to implement a strategy that can also be used by small private investors, I must develop a system that first of all contains the losses during the negative phases.

To do this, my reasoning began with an analysis of the market. The first comments were:

- The stock market development is the result of the development of the country's economy.
- The development of the country's economy is the result of the development of the individual sectors that make up the country.
- The stock market performance is the result of the performance of the individual sectors that make up it.

When the stock market grows, it does not mean that all sectors are growing simultaneously.

There will be some sectors that are growing, others that are stable, and others that are decreasing. In addition, stock market bull markets are normally driven by a few sectors that are growing very strongly.

I have therefore come to the conclusion that to do better than a given stock market you need to:

- Own the sectors that drive the upward cycles of the market and discard all others (sectoral rotation).
- Be as liquid as possible during market bearish cycles and increase exposure to dominant sectors during bullish ones.

The Sector Rotational Model

Sectoral rotation means the approach whereby capital is rotated from sectors that are doing worse than the market to sectors that are doing better. This type of approach is mainly used for investment purposes, as it produces better results considering the long time horizon. If in the short term, due to the irrationality of operators and excessive background noise, the results of this methodology are disappointing, in the long term you can appreciate all the benefits. Relative strength analysis is very well suited for carrying out sector rotation strategies.

The Relative Strength

The "relative strength" is a technical analysis tool that allows you to assess the strength of one financial instrument over another. It is nothing more than a ratio between two financial instruments that is represented by a line that can fluctuate unlimitedly above and below zero.

Figure 1. Relative Strength Line (RS Line)

When the relative strength line (called RS line) grows, it means that the instrument at the numerator is doing better than the instrument at the denominator.

Vice versa, when the RS line decreases, it means that the instrument at the denominator is doing better than the one at the numerator. The relative strength indicator is a very good medium and long-term indicator and is very useful for:

- Intermarket analysis to determine which markets (e.g., stock, bond, gold) are doing best at a given time.
- Sectoral rotation aimed at selecting those sectors that are doing better than their market of reference at a given time.
- Stock picking aimed at selecting the best shares present within the best sectors of a specific reference market.

All this information that gives us relative strength is of great importance when composing a portfolio. The relative strength is mainly used for top-down analyses (markets > sectors > shares).

So, we start from an aggregate analysis and then we go down to the individual sectors, and we finally conclude with the individual actions.

One problem that must always be taken into account when using relative strength is that a financial instrument can show greater relative strength even when its prices are falling. In fact, if the prices of this instrument are falling, but to a lesser extent than the market used for the comparison, the instrument will have a relatively greater strength. If we were to rely only on the information provided by relative strength, we would risk putting in the portfolio financial instruments that are, yes, doing better than the market of comparison, but in reality, their value is decreasing and therefore should be discarded. It follows, therefore, that the individual relative strength analysis is not sufficient but must be combined with another technique to identify price trends.

Identifying the price trend of a financial instrument you want to invest in is of fundamental importance. In fact, according to one of the most important principles of technical analysis, once a trend develops, it is more likely to continue than to reverse its direction.

Therefore, the objective of an investor must be to invest in the direction of the trends identified. But how is it possible to mechanically identify a trend?

To do this, I decided to use the Donchian Channel as an indicator.

The Donchian Channel

The Donchian channel is an indicator named after its creator, Richard Donchian. It is an indicator formed by two bands, one upper and one lower, which move according to the price trend. The upper and lower bands respectively show the maximums and minimums recorded by the prices in the last x periods (where x is a value that we choose).

Figure 2. Upper and Lower Bands of a Donchian Channel

The interpretation of the indicator is as follows:

- When prices close above the upper band of the channel, it means that a resistance has been broken and therefore that we are in the presence of a bullish trend;
- When prices close below the lower band of the channel, it means that a support has been broken and therefore that we are in the presence of a bearish trend.

Through the analysis of price movements in relation to Donchian channels, it is therefore possible to mechanically establish the beginning and end of a trend.

Figure 3. Using a Donchian Channel to Identify the Beginning and End of a Trend in Price Action

The Money Management

Relative strength and Donchian channels are not sufficient, however, to ensure the implementation of a good strategy. Any strategy that respects itself needs capital and risk management rules to avoid compromising the investor's capital during adverse market phases. Even the best strategy in the world, without proper capital management, would sooner or later lead to financial ruin.

To protect the capital, I have therefore used a very prudent capital management that allows for limiting the losses during the adverse phases of the markets.

Materials and Methods

The Timeframe

The time horizon was considered to be a period of time from 01 May 2000 to 01 March 2019. The 19-year time horizon is sufficiently high to generate an adequate number of transactions and to be able to test the strategy on all the different market phases crossed. This timeframe used is perfect for stressing the strategy, as it includes the black decade. The black decade is the period from 2000 to 2010, when the financial markets went through two of the biggest crises of all time: that of 2000 and that of 2008. Since 2000, it has also been possible to assume the worst case in which an investor had started a few weeks before the start of one of the worst periods ever. Let's take a closer look at this time horizon.

Figure 4. Dow Jones U.S. Total Market's Trends

As you can see from the graph, the time horizon 2000–2009 allows you to test the strategy on nine different phases:

- Four bullish phases
- Two bearish phases among the worst in history
- Three lateral phases in which there were strong nondirectional oscillations

The period 2000–2019 can be better broken down into the following nine phases:

- Reductionist (May 2000–September 2002) Movement: -48%
- Bullish (September 2002–October 2007) Movement: +100%
- Reductionist (October 2007–February 2009) Movement: -52%
- Bullish player (February 2009–April 2011) Movement: +92%
- Lateral (April 2011–October 2012) Movement: -18%
- Bullish (October 2012–February 2015) Movement: +50%
- Lateral (February 2015–October 2016) Movement: -10%
- Bullish (October 2016–January 2018) Movement: +32%
- Lateral (January 2018–March 2019) Movement: -15%.

Indicators

The indicators used in the strategies presented are:

- Relative strength on a weekly basis between the industry and the American stock market.
- Simple 25-period moving average of the relative strength built on the RS line.
- Donchian channel to 25 periods on a weekly basis.

Operating Rules

The operational rules used to implement this strategy can be grouped into four fields:

- Entry rules establishing the purchase of the financial instrument.
- Exit rules that establish the sale of the financial instrument.
- Capital management rules that determine how much capital to invest in each individual transaction.
- Other rules establishing further characteristics of the strategy.

There are three **buying rules:**

- The relative strength line is above its simple 25-week moving average.
- Prices close the weekly candle over the top band of the Donchian channel at 25 weeks.
- The position opens at the opening of the week following the week of the signal.

There are two **exit rules**:

- Prices close the weekly candle below the lower band of the Donchian channel at 25 weeks.
- The position closes at the opening of the week following the closing signal.

Other rules and parameters:

- Initial capital $100,000.
- Sectoral relative strength measured against Dow Jones U.S. Total Market (djus.x).
- Commissions per trade: 0%.
- Start date: 01 May 2000.
- Date of end 01 March 2019.
- Long-term only operations.
- No leverage.

Two Variations

The strategy has been presented in two versions that differ from each other in the rule of management of the capital used. Specifically, we have:

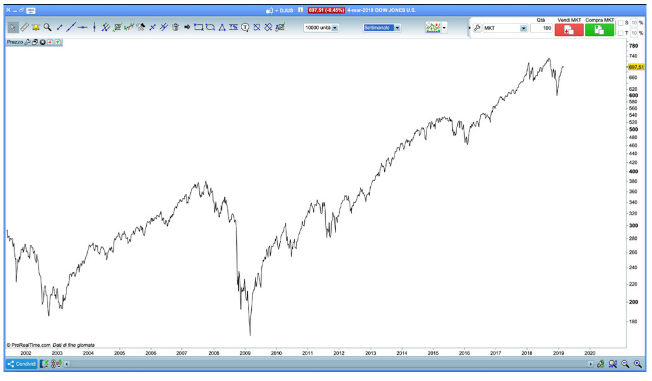
- **Fixed size strategy:** Each position weighs 5% of the initial capital.
- **Percentage size strategy:** Each position weighs 5% of the current capital.

The Benchmark

The benchmark to challenge identified for this research is the Dow Jones U.S. Total Market (djus.x).

This benchmark was chosen, as it represents the entire American stock market. Taking an index such as the S&P500 as a benchmark would have been incorrect, as it would have considered only large capitalisation companies to the exclusion of all other small and medium capitalisation companies. In the period from May 2000 to March 2019, the index achieved a performance of 107% against a maximum drawdown of 56% between October 2007 and February 2009. The graph is shown below.

Figure 5. Dow Jones U.S. Total Market in the Long Run



Financial Instruments Used

The Dow Jones indices were used to create, develop, and test the strategy. The choice fell on these on these indices, as they allowed for:

- 5A large number of sectors to be analysed.
- The study to be carried out from 2000 until 2019.

Such a broad analysis over such a long time horizon could not be carried out with indices of other companies.

The indices used were:

- Dow Jones U.S. Total Market (djus.x)
- Dow Jones U.S. Tech Hard Equipment (djustq.x)
- Dow Jones U.S. Telecom Equipment(djusct.x)
- Dow Jones U.S. Aerospace & Defence (djusae.x)
- Dow Jones U.S. Automobile (djusau.x)
- Dow Jones U.S. Basic Resource (djusbs.x)
- Dow Jones U.S. Biotech (djusbt.x)
- Dow Jones U.S. Chemicals (djusch.x)
- Dow Jones U.S. Consumer Goods (djusnc.x)
- Dow Jones U.S. Consumer Services (djuscy.x)
- Dow Jones U.S. Delivery Services (djusaf.x)
- Dow Jones U.S. Electronic Equipment (djusai.x)
- Dow Jones U.S. Financials (djusfn.x)
- Dow Jones U.S. Food & Beverage (djusfb.x)
- Dow Jones U.S. Healthcare (djushc.x)
- Dow Jones U.S. Industrials (djusin.x)
- Dow Jones U.S. Internet (djusns.x)
- Dow Jones U.S. Iron & Steel (djusst.x)
- Dow Jones U.S. Media (djusme.x)
- Dow Jones U.S. Medical Equipment (djusam.x)
- Dow Jones U.S. Oil & Gas (djusen.x)
- Dow Jones U.S. Personal Products (djuscm.x)
- Dow Jones U.S. Pharmaceuticals (djuspr.x)
- Dow Jones U.S. Railroads (djusrr.x)
- Dow Jones U.S. Real Estate(djusre.x)
- Dow Jones U.S. Restaurants & Bars (djusru.x)
- Dow Jones U.S. Retail (djusrt.x)
- Dow Jones U.S. Semiconductor (djussc.x)
- Dow Jones U.S. Software (djussw.x)
- Dow Jones U.S. Specialty Retailers (djusrs.x)
- Dow Jones U.S. Technology (djustc.x)
- Dow Jones U.S. Telecommunications (djustl.x)
- Dow Jones U.S. Travel & Leisure (djuscg.x)
- Dow Jones U.S. Utilities (djusut.x)

The Platform

The Multicharts platform was used to conduct the research, run the tests and analyse the results. The choice fell on this platform as it is considered among the most complete and reliable among all those on the market. The use of an efficient and performing platform is of fundamental importance to perform a complete and reliable search.

Historical Data Feed

The history of data on all indices used in the search was provided by the iqfeed.net service.

The choice fell on this supplier of historical data, as it is considered one of the most reliable among all those on the market.

To carry out decent research, it is necessary to start from very good quality historical data; otherwise, you would risk having results distorted by reality and therefore be unreliable.

Results

Fixed Size Strategy

Performance Analysis

Let's start with the simulation of the strategy applying the variant of the Fixed Size. In this simulation, each size weighs 5% of the initial capital and therefore, each size is equal to $5,000. From the table below we can see the analysis of the trades made.

As you can see, 233 operations have been done, all long. 136 transactions were closed for profit, and only 97 transactions were closed for loss. The percentage of closed operations in profit was 58%. A decidedly high value for a trend-following strategy! Also important is the ratio between the average of closed operations in profit and the average of closed operations in loss, which stands at 4.5. This means that for every euro lost on average in a losing trade, there is an average of €4. 5 earned for every trade closed for profit.

The balance between the values of Percent Profitable and Ratio Avg. Win Avg Loss is truly exceptional.

Table 3 presents the "Performance Summary." The important data in this table are:

- The return on initial capital of $100,000 was 220%, which equates to an average annual return of 12.55%.
- Starting from a capital of $100,000, the capital really needed to perform the operations was only $25,800 (or almost 26% of the initial capital).
- The return on capital actually required was 852%.
- The maximum drawdown measured, also considering the operations still open, was 18.86% and was recorded during the "financial earthquakes" of 2010.
- The maximum drawdown measured considering only closed positions was 11.7%.
- The profit factor, i.e., the ratio between profits and losses obtained by the strategy, is equal to 6.34%.
- The total yield obtained was 5.43 times the maximum drawdown sustained. In the light of these data, we can say that we are facing an excellent trend.
- Following strategy, which is able not only to contain losses, but also to let the profits run.
  Performance Ratio Analysis

Let's now deal with the analysis of the Performance Ratios shown in the Table 4.

As you can see from the table, the strategy has an Upside Potential Ratio of 40.24 which represents a very positive value. The annualised Sharpe Ratio and the Sortino Ratio also showed positive values of 0.53 and 0.23 respectively.

Time Analysis

We now move on to the Time Analysis shown in Table 5.

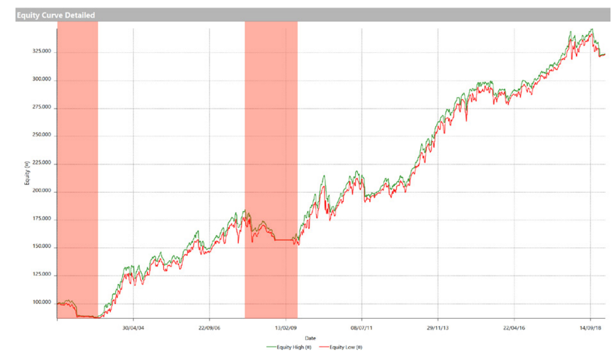
The time period between the first and last trade was 17 years and 7 months. Of this time span, the actual period on the market was 16 years and 9 months, equal to 5% of the total time. The longest period in which we stayed flat was 5 months and 25 days. The day with the worst drawdown was February 7, 2010, while the day with the best run-up was May 10, 2018.

Equity Curve Detailed

Let's take care of the visual aspect now. We move on to the analysis of the equity line shown in the Figure 6.

In the chart, you can see the trend of the equity line of the portfolio from the initial

Figure 6. Equity Curve Detailed of the Simulation



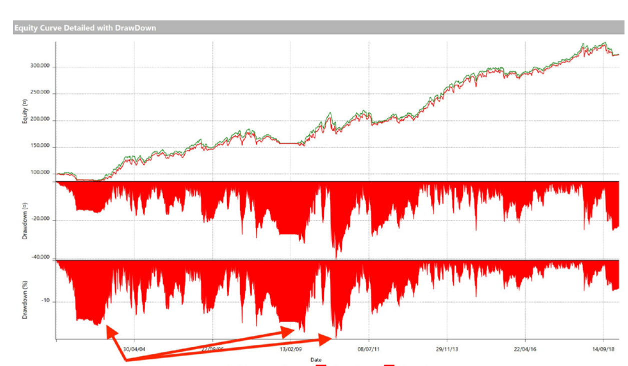
$100,000 up to the final $325,000. The red rectangles show the two major financial crises of 2000 and 2008. As we can see, during these extremely negative phases in which markets usually lose more than 50%, the strategy succeeds in significantly limiting losses.

The strength of the strategy is precisely in these bearish phases of the markets in which it succeeds in progressively reducing the exposure until it remains completely uninvested (flat) during the most acute final moments of the crises. Containing losses when markets halve their value is a great strength because it allows you to recover faster than previous highs, when markets start to rise again. The strategy succeeds in doing all this thanks to the sector rotation and the use of liquidity in the negative moments in the markets.

Drawdown Analysis

In Figure 7, we can analyze the drawdowns in detail.

Figure 7. Equity Curve Detailed With Drawdown of the Simulation



The biggest drawdowns were 3, and they all occurred during the crises of 2000 and 2008 and during the shocks of 2010. From 2012 onwards, all maximum drawdowns remained below 10%. This is due both to a particularly prosperous period for the markets, but also to the fact that the percentage of total capital invested in each individual trade, since the size is fixed at $5,000, decreases as the accumulated capital increases.

Table 2. Total Trade Analysis of the Strategy Simulation

Total Trade Analysis	All Trades	Long Trades	Short Trades
Total # of Trades	233	233	0
Total # of Open Trades	6	6	0
Number Winning Trades	136	136	0
Number Losing Trades	97	97	0
Percent Profitable	58,37%	58,37%	0%
Avg Trade (win loss)	944,87 ¤	944,87 ¤	,00 ¤
Average Winning Trade	1.922,00 ¤	1.922,00 ¤	,00 ¤
Average Losing Trade	(425,12 ¤)	(425,12 ¤)	,00 ¤
Ratio Avg Win / Avg Loss	4,52	4,52	0

Table 3. Performance Summary of the Strategy Simulation

Performance Summary	All Trades	Long Trades	Short Trades
Net Profit	220.155,39 ¤	220.155,39 ¤	,00 ¤
Gross Profit	261.391,92 ¤	261.391,92 ¤	,00 ¤
Gross Loss	(41.236,53 ¤)	(41.236,53 ¤)	,00 ¤
Account Size Required	25.819,53 ¤	25.819,53 ¤	,00 ¤
Return on Account	852,67%	852,67%	0%
Return on Initial Capital	220,16%	220,16%	0%
Profit Factor	6,34	6,34	0
Slippage Paid	,00 ¤	,00 ¤	,00 ¤
Commission Paid	,00 ¤	,00 ¤	,00 ¤
Open Position P/L	3.695,19 ¤	3.695,19 ¤	,00 ¤
Select Net Profit	122.092,93 ¤		
Adjusted Net Profit	193.554,29 ¤		
Max Portfolio Drawdown	(40.557,58 ¤)		
Max Portfolio Drawdown (%)	(18,86%)		
Max Portfolio Close To Close Drawdown	(11.722,58 ¤)		
Max Portfolio Close To Close Drawdown (%)	(11,72%)		
Return on Max Portfolio Drawdown	5,43		
Annual Rate of Return	12,55%		

Table 4. Performance Ratio of the Strategy Simulation

Performance Ratios	
Upside Potential Ratio	40,24
Sharpe Ratio	,15
Annualized Sharpe Ratio	,53
Sortino Ratio	,23
Fouse Ratio	0
Calmar Ratio	,02
Sterling Ratio	0
Portfolio Net Profit as % of Largest loss	12820,6%
Portfolio Net Profit as % of Max Trade Drawdown	4510,26%
Portfolio Net Profit as % of Max Portfolio Drawdown	542,82%
Select Net Profit as % of Largest loss	7110%
Select Net Profit as % of Max Trade Drawdown	2501,28%
Select Net Profit as % of Max Strategy Drawdown	301,04%
Adj Net Profit as % of Largest loss	11271,51%
Adj Net Profit as % of Max Trade Drawdown	3965,29%
Adj Net Profit as % of Max Strategy Drawdown	477,23%

Table 5. Time Analysis of the Strategy Simulation

Time Analysis	
Trading Period	17 Yrs, 7 Mths, 3 Dys
Time in the Market	16 Yrs, 9 Mths, 20 Dys
Percent in the Market	95,52%
Longest flat period	5 Mths, 25 Dys
Max Run-up Date	05/10/18
Max Portfolio Drawdown Date	02/07/10
Max Close To Close Drawdown Date	11/10/02

Annual Rolling Period Analysis

Another interesting table is the one relating to the Annual Rolling Period Analysis, which is shown below.

Table 6. Annual Rolling Period Analysis of the Simulation

Annual Rolling Period Analysis

Period	Net Profit	% Profit	Profit Factor	# Trades	Percent Profitable
Today - 2019	1.587,64 ¤	,49%	16,49	6	66,67%
2018 - 2019	(4.473,67 ¤)	(1,36%)	(,59)	37	27,03%
2017 - 2019	26.833,58 ¤	9,03%	6,03	44	61,36%
2016 - 2019	32.979,45 ¤	11,34%	4,53	58	51,72%
2015 - 2019	31.894,04 ¤	10,92%	2,88	75	48%
2014 - 2019	58.082,00 ¤	21,85%	5,3	87	55,17%
2013 - 2019	116.808,55 ¤	56,42%	13,5	89	65,17%
2012 - 2019	124.079,04 ¤	62,11%	11,11	96	62,5%
2011 - 2019	121.892,10 ¤	60,36%	7,22	120	51,67%
2010 - 2019	132.022,82 ¤	68,82%	6,1	136	54,41%
2009 - 2019	166.688,74 ¤	106,06%	11,16	136	63,97%
2008 - 2019	146.615,27 ¤	82,72%	4,72	164	54,27%
2007 - 2019	166.742,66 ¤	106,13%	6,94	174	56,9%
2006 - 2019	179.308,40 ¤	124,05%	7,2	192	55,21%
2005 - 2019	182.693,74 ¤	129,43%	6,22	202	57,43%
2004 - 2019	201.430,36 ¤	164,54%	6,27	221	56,56%
2003 - 2019	235.542,56 ¤	266,73%	9,21	221	62,9%
2002 - 2019	223.253,26 ¤	221,93%	6,15	239	58,16%
2001 - 2019	223.850,58 ¤	223,85%	8,7	239	58,16%

As can be seen from Table 6, applying the strategy from any year to date, no negative results would have been achieved.

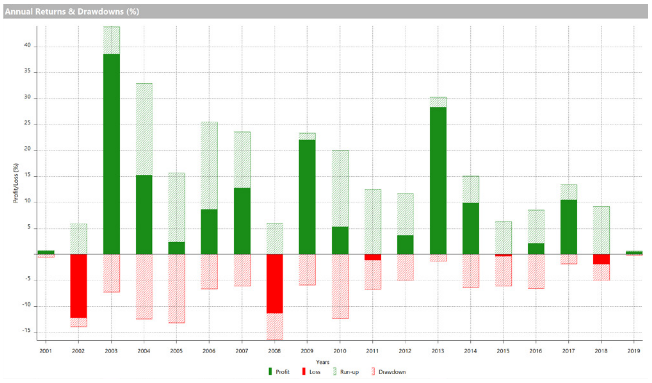
The percentage of profitable trades always remains significantly above 50%, reaching over 60% in some cases. The same applies to Profit Factors, always above 4 until reaching a peak of 11 for departures in 2009 or 2012. Only in the case of startups in 2015 and 2018 would the results have been less than exciting with the percentages of profitable trade that fall below 50% and profit factors that go below 4. In fact, starting in 2018 would have been the only case in which the strategy would have led to negative returns (-1.36%).

To be fair, 1 year and 3 months is a too short a period of time to evaluate a long-term approach that takes at least 5 years to express itself at best.

Annual Returns and Drawdown Analysis

If you break down the performance year by year, you get the histogram shown in Figure 8.

Figure 8. Annual Return and Drawdown (%)



As can be seen from the graph, only 5 of the 19 years of operation have generated losses. In these 5 years, losses of less than 5% have been recorded three times and losses of between 10% and 15% have been recorded two times. The remaining 14 years have all produced positive returns. Of these 14 years, the best were 2003, with a performance of over 35%, and 2013, with a performance of over 25%.

Monte Carlo Analysis

Two Monte Carlo tests were conducted, both based on 100,000 simulations. The first was conducted on 100% of trades made. The second was conducted on 95% of all trades done. You can see the results in Figures 9 and 10.

Figure 9. Montecarlo Analysis Based on 100,000 Simulations and 100% of the Trades

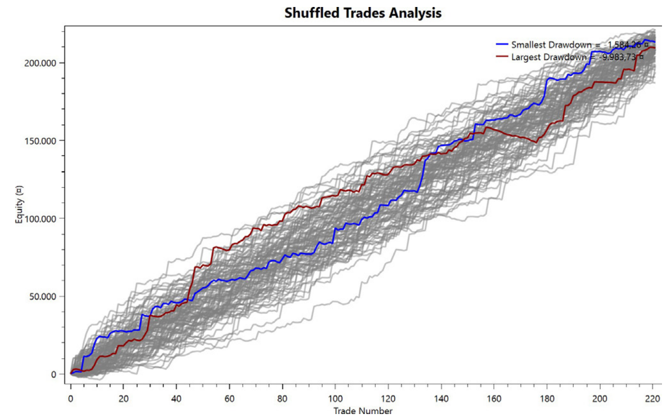
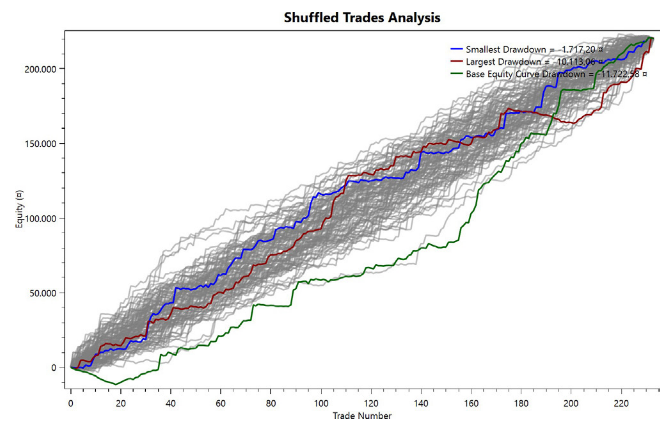


Figure 10. Monte Carlo Analysis Based on 100,000 Simulations and 95% of All Trades



As you can see from the graphs, the Monte Carlo simulations confirm the goodness of the strategy.

Sector-by-Sector Analysis

Let's deepen the analysis by going into more detail. Table 7 shows the results of the sector-by-sector strategy.

Table 7. Sector-by-Sector Analysis

Market	Start Date	End Date	Net Profit	# Trades
DJUSTQ.X	24/11/06	01/03/19	6.845,49 ¤	5
DJUSCT.X	06/06/03	01/03/19	1.786,97 ¤	9
DJUSAE.X	22/02/02	01/03/19	7.579,61 ¤	7
DJUSAU.X	26/04/02	01/03/19	4.763,30 ¤	7
DJUSBS.X	18/07/03	01/03/19	3.046,46 ¤	8
DJUSBT.X	28/03/03	01/03/19	7.457,65 ¤	11
DJUSCG.X	23/05/03	01/03/19	12.394,83 ¤	4
DJUSCH.X	08/03/02	01/03/19	4.474,63 ¤	8
DJUSNC.X	28/12/01	01/03/19	4.486,63 ¤	6
DJUSCY.X	15/03/02	01/03/19	6.878,21 ¤	7
DJUSAF.X	14/12/01	01/03/19	3.518,05 ¤	7
DJUSAI.X	11/01/02	01/03/19	5.917,14 ¤	9
DJUSFN.X	15/03/02	01/03/19	5.898,46 ¤	5
DJUSFB.X	01/03/02	01/03/19	5.461,46 ¤	5
DJUSHC.X	09/05/03	01/03/19	4.397,44 ¤	8
DJUSIN.X	15/03/02	01/03/19	6.419,24 ¤	7
DJUSNS.X	28/03/03	01/03/19	22.465,39 ¤	6
DJUSST.X	05/04/02	01/03/19	13.046,38 ¤	9
DJUSME.X	23/05/03	01/03/19	7.140,47 ¤	7
DJUSAM.X	07/12/01	01/03/19	7.924,69 ¤	8
DJUSUT.X	30/05/03	01/03/19	4.099,81 ¤	5
DJUSEN.X	15/03/02	01/03/19	7.632,75 ¤	9
DJUSCM.X	29/03/02	01/03/19	2.877,57 ¤	8
DJUSPR.X	13/02/04	01/03/19	3.715,58 ¤	6
DJUSRR.X	08/02/02	01/03/19	12.395,52 ¤	6
DJUSRE.X	15/03/02	01/03/19	3.682,30 ¤	8
DJUSRU.X	11/01/02	01/03/19	8.951,84 ¤	4
DJUSRT.X	04/01/02	01/03/19	5.319,98 ¤	8
DJUSSC.X	13/06/03	01/03/19	4.031,33 ¤	8
DJUSSW.X	29/11/02	01/03/19	10.695,71 ¤	6
DJUSRS.X	14/12/01	01/03/19	7.910,32 ¤	8
DJUSTC.X	13/06/03	01/03/19	4.416,28 ¤	9
DJUSTL.X	16/01/04	01/03/19	2.523,90 ¤	5

As can be seen from the table, even if we break down the operations by sector, no single sector has ever produced negative results in 19 years of operation.

For those who love statistics and data, there are two tables—Tables 8 and 9—for learning more about the operation of each individual sector.

Table 8. Equity Curve Analysis

Equity Curve Analysis

Market	Max. Equity Drawdown (¤)	Max. Equity Drawdown (%)	Max. Equity Run-up (¤)	Max. Equity Run-up(%)	Avg. Monthly Return	Std. Dev. of Returns
DJUSTQ.X	(1.783,50 ¤)	(1,64%)	8.819,25 ¤	8,85%	47,21 ¤	276,35 ¤
DJUSCT.X	(4.079,65 ¤)	(3,93%)	3.916,68 ¤	3,92%	9,56 ¤	266,79 ¤
DJUSAE.X	(3.565,46 ¤)	(3,35%)	10.558,97 ¤	10,66%	37,34 ¤	288,24 ¤
DJUSAU.X	(4.799,30 ¤)	(4,47%)	9.002,13 ¤	9,16%	24,81 ¤	360,10 ¤
DJUSBS.X	(3.297,82 ¤)	(3,2%)	4.655,79 ¤	4,67%	16,74 ¤	348,77 ¤
DJUSBT.X	(3.304,57 ¤)	(3,23%)	11.007,22 ¤	11,12%	39,25 ¤	350,31 ¤
DJUSCG.X	(1.885,20 ¤)	(1,67%)	13.860,81 ¤	13,89%	65,93 ¤	318,19 ¤
DJUSCH.X	(1.749,34 ¤)	(1,71%)	6.161,69 ¤	6,21%	23,18 ¤	232,93 ¤
DJUSNC.X	(1.033,76 ¤)	(1,02%)	5.776,62 ¤	5,8%	22,89 ¤	169,50 ¤
DJUSCY.X	(1.377,42 ¤)	(1,35%)	8.832,18 ¤	8,89%	34,05 ¤	213,25 ¤
DJUSAF.X	(2.175,93 ¤)	(2,1%)	5.230,38 ¤	5,24%	17,95 ¤	233,72 ¤
DJUSAI.X	(2.423,54 ¤)	(2,39%)	8.242,91 ¤	8,33%	29,15 ¤	277,23 ¤
DJUSFN.X	(1.314,40 ¤)	(1,28%)	7.370,53 ¤	7,42%	29,35 ¤	184,08 ¤
DJUSFB.X	(1.575,72 ¤)	(1,57%)	7.945,60 ¤	8,03%	29,21 ¤	195,90 ¤
DJUSHC.X	(2.541,78 ¤)	(2,39%)	6.694,42 ¤	6,72%	23,39 ¤	218,69 ¤
DJUSIN.X	(1.399,55 ¤)	(1,36%)	8.389,64 ¤	8,47%	31,94 ¤	212,72 ¤
DJUSNS.X	(6.949,80 ¤)	(6,32%)	24.296,99 ¤	24,33%	118,86 ¤	499,28 ¤
DJUSST.X	(4.570,15 ¤)	(4,24%)	15.611,50 ¤	15,76%	65,56 ¤	554,85 ¤
DJUSME.X	(5.220,02 ¤)	(5,17%)	9.339,31 ¤	9,39%	37,98 ¤	259,86 ¤
DJUSAM.X	(1.669,80 ¤)	(1,56%)	9.914,50 ¤	10%	38,66 ¤	255,68 ¤
DJUSUT.X	(2.196,97 ¤)	(2,09%)	5.622,83 ¤	5,64%	23,19 ¤	208,51 ¤
DJUSEN.X	(3.211,55 ¤)	(2,92%)	11.262,29 ¤	11,39%	37,97 ¤	321,95 ¤
DJUSCM.X	(2.014,35 ¤)	(1,98%)	5.358,79 ¤	5,4%	15,23 ¤	207,69 ¤
DJUSPR.X	(1.821,48 ¤)	(1,73%)	6.587,70 ¤	6,68%	22,13 ¤	191,74 ¤
DJUSRR.X	(2.983,58 ¤)	(2,81%)	15.047,16 ¤	15,16%	59,76 ¤	380,47 ¤
DJUSRE.X	(1.816,41 ¤)	(1,75%)	5.616,97 ¤	5,65%	17,87 ¤	210,18 ¤
DJUSRU.X	(1.818,72 ¤)	(1,74%)	13.243,10 ¤	13,34%	60,03 ¤	266,42 ¤
DJUSRT.X	(1.625,16 ¤)	(1,55%)	7.527,20 ¤	7,61%	26,21 ¤	218,40 ¤
DJUSSC.X	(3.307,11 ¤)	(3,22%)	6.087,70 ¤	6,12%	21,67 ¤	287,83 ¤
DJUSSW.X	(1.988,92 ¤)	(1,94%)	12.495,48 ¤	12,62%	55,13 ¤	287,63 ¤
DJUSRS.X	(2.039,82 ¤)	(1,88%)	9.586,68 ¤	9,64%	38,78 ¤	281,36 ¤
DJUSTC.X	(2.163,35 ¤)	(2,12%)	5.978,59 ¤	6%	23,74 ¤	226,61 ¤
DJUSTL.X	(1.812,24 ¤)	(1,75%)	3.941,11 ¤	3,96%	12,05 ¤	191,16 ¤

Table 9. Sector-by-Sector Ratio Analysis

Ratios

Market	Upside Potential	Sharpe Ratio	Annualized Sharpe Ratio	Sortino Ratio	Fouse Ratio	Calmar Ratio	Sterling Ratio	Avg.Win /Avg. Loss	Profit Factor	Percent Profitable
DJUSTQ.X	70,02	(,45)	(1,57)	(,6)	0	,18	0	26,74	40,11	60%
DJUSCT.X	49,22	(,6)	(2,07)	(,79)	0	,18	0	2,13	1,7	44,44%
DJUSAE.X	59,79	(,47)	(1,64)	(,59)	0	,19	0	3,35	4,47	57,14%
DJUSAU.X	78,49	(,4)	(1,39)	(,73)	0	,28	0	2,7	3,6	57,14%
DJUSBS.X	69,34	(,44)	(1,51)	(,65)	0	,16	0	2,9	4,83	62,5%
DJUSBT.X	73,57	(,38)	(1,32)	(,55)	0	,17	0	4,8	2,74	36,36%
DJUSCG.X	99,19	(,35)	(1,22)	(,53)	0	,2	0	35,3	105,89	75%
DJUSCH.X	49	(,63)	(2,18)	(,8)	0	,22	0	1,77	5,3	75%
DJUSNC.X	37,62	(,87)	(3,01)	(1,11)	0	,2	0	6,68	13,36	66,67%
DJUSCY.X	56,26	(,65)	(2,25)	(,85)	0	,2	0	4,71	11,79	71,43%
DJUSAF.X	51,13	(,65)	(2,27)	(,87)	0	,13	0	6,19	4,64	42,86%
DJUSAI.X	64,76	(,51)	(1,77)	(,7)	0	,13	0	1,86	3,71	66,67%
DJUSFN.X	41,15	(,77)	(2,67)	(,96)	0	,24	0	2,6	10,4	80%
DJUSFB.X	46,58	(,72)	(2,5)	(,91)	0	,15	0	10,16	6,77	40%
DJUSHC.X	46,08	(,68)	(2,35)	(,85)	0	,16	0	3,04	5,07	62,5%
DJUSIN.X	53,78	(,66)	(2,28)	(,86)	0	,18	0	4,91	6,54	57,14%
DJUSNS.X	125,65	(,13)	(,45)	(,21)	0	,14	0	10,56	52,79	83,33%
DJUSST.X	86,17	(,2)	(,7)	(,32)	0	,23	0	7,18	5,75	44,44%
DJUSME.X	65,25	(,52)	(1,81)	(,69)	0	,27	0	3,9	9,74	71,43%
DJUSAM.X	65,52	(,53)	(1,83)	(,71)	0	,2	0	5,3	8,83	62,5%
DJUSUT.X	43,09	(,71)	(2,48)	(,9)	0	,4	0	17,18	25,77	60%
DJUSEN.X	80,01	(,42)	(1,47)	(,66)	0	,18	0	6,25	3,12	33,33%
DJUSCM.X	45,33	(,74)	(2,57)	(,98)	0	,41	0	3,64	2,18	37,5%
DJUSPR.X	54,33	(,77)	(2,66)	(1,11)	0	,23	0	15,04	3,01	16,67%
DJUSRR.X	72,22	(,31)	(1,07)	(,38)	0	,15	0	5,95	29,73	83,33%
DJUSRE.X	39,56	(,73)	(2,52)	(,9)	0	,43	0	2,93	4,88	62,5%
DJUSRU.X	87,8	(,43)	(1,51)	(,62)	0	,21	0	12,62	12,62	50%
DJUSRT.X	59,62	(,66)	(2,28)	(,94)	0	,15	0	3,57	5,94	62,5%
DJUSSC.X	63,96	(,51)	(1,78)	(,75)	0	,15	0	2,36	3,94	62,5%
DJUSSW.X	82,09	(,41)	(1,43)	(,59)	0	,12	0	10,28	20,57	66,67%
DJUSRS.X	82,06	(,48)	(1,65)	(,75)	0	,19	0	3,81	11,43	75%
DJUSTC.X	51,17	(,65)	(2,23)	(,84)	0	,18	0	4,87	6,09	55,56%
DJUSTL.X	38,91	(,82)	(2,85)	(1,06)	0	,26	0	1,54	6,18	80%

The sector on which the strategy worked best was the sector Dow Jones U.S. Internet (djusns.x), which produced a yield of 24% compared to a Drawdown of 6.3%. The sector on which the strategy worked worst was the Dow Jones U.S. Telecom Equipment sector (djusct.x), which produced a yield of 3.9% compared to a drawdown of 3.9%.

Percentage Size Strategy

Performance Summary Analysis

What we just saw was the strategy applied using a fixed size for each operation of $5,000. Let's now see the results obtained applying the strategy in the variant Percentage Size. Table 10 shows the comparative results of the two simulations.

Table 10. Comparison Between Fixed Size Strategy and Variable Size Strategy

	Fixed size of 5.000$	Size of 5%
Return on initial capital	220%	422%
Account size required	25.800$ (25,8%)	53.600$ (53%)
Return on account required	852%	787%
Profit Factor	6,34	6,18
Annual rate return	12,6%	24%
Max drawdown	18,9%	26,5%
Max close to close drawdown	11,7%	11,8%
Annualized Sharpe ratio	0,53	0,6
Sortino Ratio	0,23	0,26
Upside potential ratio	40,24	27,6

From the comparison, it is evident that by using a percentage rather than fixed measure, it is possible to obtain a double average annual yield compared to a close to

close drawdown practically identical. The profit factor is not subject to significant changes. There is a slight improvement in the Sharpe Ratio and Sortino Ratio. The capital required to execute the strategy with the size in percentage measure doubles, going from 25% of the initial capital for the fixed size strategy up to 53%.

Statistical Data

For the sake of completeness of information, the most relevant statistical data of the strategy with the size in percentage is shown in Tables 11 and 12.

Table 11. Performance Summary of Percentage Size Simulation

Performance Summary	All Trades	Long Trades	Short Trades
Net Profit	422.477,25 ¤	422.477,25 ¤	,00 ¤
Gross Profit	504.020,55 ¤	504.020,55 ¤	,00 ¤
Gross Loss	(81.543,30 ¤)	(81.543,30 ¤)	,00 ¤
Account Size Required	53.654,73 ¤	53.654,73 ¤	,00 ¤
Return on Account	787,4%	787,4%	0%
Return on Initial Capital	422,48%	422,48%	0%
Profit Factor	6,18	6,18	0
Slippage Paid	,00 ¤	,00 ¤	,00 ¤
Commission Paid	,00 ¤	,00 ¤	,00 ¤
Open Position P/L	16.065,96 ¤	16.065,96 ¤	,00 ¤
Select Net Profit	226.665,22 ¤		
Adjusted Net Profit	370.525,96 ¤		
Max Portfolio Drawdown	(129.068,74 ¤)		
Max Portfolio Drawdown (%)	(26,48%)		
Max Portfolio Close To Close Drawdown	(11.822,82 ¤)		
Max Portfolio Close To Close Drawdown (%)	(11,82%)		
Return on Max Portfolio Drawdown	3,27		
Annual Rate of Return	24,09%		

Table 12. Performance Ratios of Percentage Size Simulation

Performance Ratios	
Upside Potential Ratio	27,62
Sharpe Ratio	,17
Annualized Sharpe Ratio	,6
Sortino Ratio	,26
Fouse Ratio	,01
Calmar Ratio	,02
Sterling Ratio	0
Portfolio Net Profit as % of Largest loss	6192,73%
Portfolio Net Profit as % of Max Trade Drawdown	6192,73%
Portfolio Net Profit as % of Max Portfolio Drawdown	327,33%
Select Net Profit as % of Largest loss	3322,49%
Select Net Profit as % of Max Trade Drawdown	3322,49%
Select Net Profit as % of Max Strategy Drawdown	175,62%
Adj Net Profit as % of Largest loss	5431,22%
Adj Net Profit as % of Max Trade Drawdown	5431,22%
Adj Net Profit as % of Max Strategy Drawdown	287,08%

Figure 11. Equity Curve Detailed With Drawdown of Percentage Size Simulation

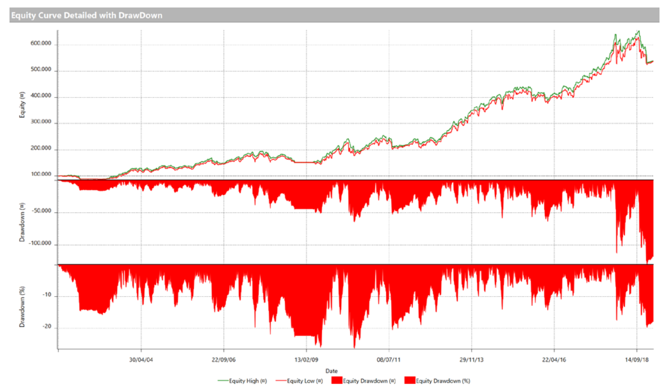


Table 13. Annual Rolling Period Analysis of Percentage Size Simulation

Annual Rolling Period Analysis

Period	Net Profit	% Profit	Profit Factor	# Trades	Percent Profitable
Today - 2019	8.276,54 ¤	1,56%	14,73	6	66,67%
2018 - 2019	(30.002,25 ¤)	(5,28%)	(,43)	36	27,78%
2017 - 2019	97.921,10 ¤	22,22%	4,54	42	61,9%
2016 - 2019	124.606,78 ¤	30,1%	4,02	56	51,79%
2015 - 2019	118.172,87 ¤	28,11%	2,85	73	47,95%
2014 - 2019	180.792,88 ¤	50,54%	4,74	84	55,95%
2013 - 2019	306.406,80 ¤	131,99%	8,75	86	66,28%
2012 - 2019	320.967,07 ¤	147,52%	7,98	93	63,44%
2011 - 2019	314.927,62 ¤	140,83%	6,19	117	52,14%
2010 - 2019	332.892,91 ¤	161,87%	5,81	133	54,89%
2009 - 2019	386.778,08 ¤	254,85%	8,09	133	64,66%
2008 - 2019	353.520,95 ¤	191,07%	5,02	160	54,37%
2007 - 2019	379.847,12 ¤	239,36%	6,54	169	57,99%
2006 - 2019	395.073,57 ¤	275,37%	6,69	187	56,15%
2005 - 2019	400.799,95 ¤	290,98%	6	198	58,08%
2004 - 2019	418.997,89 ¤	350,49%	6,08	216	56,94%
2003 - 2019	450.295,04 ¤	510,26%	7,49	216	63,43%
2002 - 2019	437.945,89 ¤	435,35%	6,78	234	58,55%
2001 - 2019	438.543,21 ¤	438,54%	10,86	234	58,55%

Figure 12. Monte Carlo Analysis Based on 100,000 Simulations and 95% of the All Trades

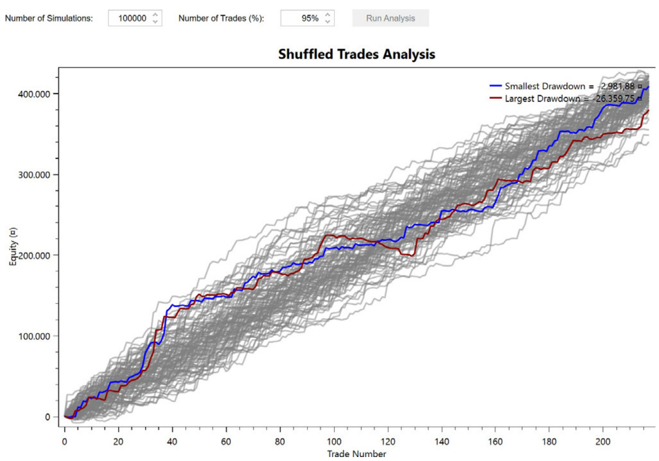
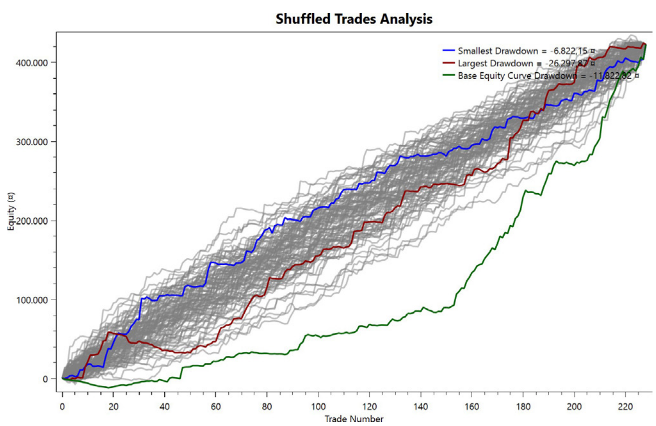


Figure 13. Monte Carlo Analysis Based on 100,000 Simulations and 100% of All Trades

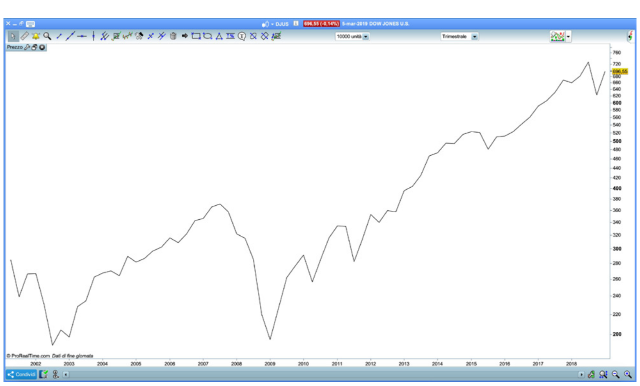


Comparison With the Benchmark

Let's now make the long-awaited comparison against the stated benchmark that is the Dow Jones U.S. Total Market (Djus.x).

In Figure 14, it is possible to observe the trend of the djus.x index on a quarterly basis from 2000 until 2019.

Figure 14. Dow Jones U.S. Total Market in Quarter-by-Quarter Timeframe



During this period, the index produced a yield of 107% compared to a maximum drawdown of 56% during the 2008 crisis.

Table 14. Comparison Between djus.x, Fixed Size Strategy and Percentage Size Strategy

	Fixed size strategy	Percentage size strategy	Djus.x
Return	220%	422%	107%
Max drawdown	18,9%	26,5%	56%

As we can see from the comparative table, both strategies (with fixed size and with size in percentage) have produced much higher yields in the face of risks more than halved. We can therefore say that a sector rotation supported by technical analysis tools allows for significantly better results than a simple strategy of buy & hold of the entire market.

This advantage was achieved through a sector rotation technique in favour of sectors that are on trend and by liquidity assistance when the market enters bearish phases.

Discussion

Comparison With the Best Actively Managed Funds

In this section, I want to make a comparison of the strategy against the best active fund present since 2000 to date.

To do this, I went to morningstar.com and did a search by selecting the following as parameters:

- Equity Use Flex Cap
- Retail Funds

Then I did a search to find the best active dividend accumulation fund and the best active dividend distribution fund with a history from May 2000 until March 2019. The results were these two funds:

- PGIM Jennison U.S. All Cap Equity Fund USD I Accumulation
- WIP Opportunistic Equity Fund A Distribution

Figures 15 and 16 show the price development of the two funds.

Figure 15. Pgim Jennison U.S. All Cap Fund From 2000 to 2019

Figure 16. Wip Opportunistic Equity A Fund From 2000 to 2019

Let's now compare the two funds and the two strategies in Table 15.

Table 15. Comparison Between Fixed Size Strategy, Percentage Size Strategy, Pgim Fund, and Wip Fund

2000 - 2019	Size fissa	Size %	Fondo Pgim (Acc)	Fondo Wip (Dis)
Return	220%	422%	270%	130%
Drawdown	18,9%	26,5%	52%	53%

The following observations can be made from the analysis of the comparative table:

- The strategy with the percentage size proves to be better than both funds. It has higher yields for lower risks.
- The fixed-size strategy proves to be significantly less risky than both funds with a maximum drawdown of more than half that. The return side, on the other hand, proves to be higher than the Wip fund for the distribution of dividends, but lower than the Pgim fund for the accumulation of dividends. It must be said that the test of strategies was done on price indices that do not consider the reinvestment of dividends in their value, so probably the best comparison would be with the Wip fund to distribute dividends.

How to Use the Strategy in Reality

Introduction of the ETFs

What we have seen so far has been an analysis of the value of the sectoral indices that in reality cannot be bought on the market. I can't go to market tomorrow and buy the Dow Jones U.S. Internet Index. So, after making sure that the strategy worked, as we saw a moment ago, I went to test it with tools that could really be bought on the market by anyone. To do this, I used the sectoral ETF (Exchange Traded Funds), i.e., those funds that passively replicate the trend of the sectoral indices.

The ETF used for the research were:

- xlv: health care select sector spdr
- xlk: technology select sector spdr
- vgt: vanguard information technolog
- xle: energy select sector spdr
- xly: spdr consumer discret select
- xlu: utilities select sector spdr
- ibb: ishares nasdaq biotechnology
- fdn: first trust dow jones internet
- ita: i shares us aerospace & defense
- ihi: ishares dow jones us medical d
- kre: spdr s&p regional banking ETF
- igv: ishares north american tech-software ETF
- kbe: spdr s&p bank ETF
- xop: spdr s&p oil & gas exploration
- skyy: first trust cloud computin
- hack: aftmg ise cyber security ETF
- iyg: ishares dow jones us financial
- vox: vanguard communication services ETF
- soxx: ishares phlx semiconductor ETF
- itb: i shares us home construction
- ihf: ishares dow jones us healthcar
- pho: powershares water resources portfolio
- ige: ishares north american natural resources ETF
- kie: spdr s&p insurance ETF
- xhe: spdr s&p health care equipment
- xhb: spdr s&p homebuilders
- iyz: ishares u.s. telecommunications ETF
- iyk: ishares dow jones us consumer
- xrt: spdr s&p retail
- ipay: aftmg ise mobile payments ETF
- arkg: ark genomic revolution multi-s
- fxg: first trust consumer staples a
- finx: global x fintech ETF
- ibuy: amplify online retail ETF
- iai: ishares dow jones us broker-de
- psp: invesco global listed priv
- ring: ishares msci global gold miner
- pzd: invesco cleantech
- pkb: invesco dynamic building & construction
- iak: ishares dow jones us insurance
- xtl: spdr s&p telecom
- pej: invesco dynamic leisure
- pbj: invesco dynamic food & bev
- pxq: invesco dynamic networking
- pbs: invesco dynamic media
- silj: aftmg ise junior silver
- fill: ishares msci global energy pro
- bbc: bioshares biotechnology clinic
- pjp: invesco dynamic pharmaceut
- blok: amplify transformational data sharing ETF

Methods and Criteria

The simulation was conducted according to the following parameters:

- Initial capital $100,000
- Relative strength measured against Dow Jones U.S. Total Market (djus.x)
- Relative strength moving average 25 periods
- Donchian channel 25 periods
- Size single positions 5%
- Commissions per trade: 0.5%
- Start date: 01 January 2008
- Date of end 01 March 2019

Commissions of 0.5% have been included to make the simulation as realistic as possible. The starting date of the simulation is January 1, 2009, because it is not possible to find enough ETF for previous starting dates.

Results

The obtained results are shown in the following tables and figures.

Table 16. Performance Summary of ETF Simulation

Performance Summary	All Trades
Net Profit	275.924,13 ¤
Gross Profit	347.652,64 ¤
Gross Loss	(71.728,52 ¤)
Account Size Required	57.607,52 ¤
Return on Account	478,97%
Return on Initial Capital	275,92%
Profit Factor	4,85
Slippage Paid	,00 ¤
Commission Paid	17.091,00 ¤
Open Position P/L	3.995,99 ¤
Select Net Profit	170.769,93 ¤
Adjusted Net Profit	231.220,78 ¤
Max Portfolio Drawdown	(147.071,16 ¤)
Max Portfolio Drawdown (%)	(33,11%)
Max Portfolio Close To Close Drawdown	(16.122,19 ¤)
Max Portfolio Close To Close Drawdown (%)	(16,12%)
Return on Max Portfolio Drawdown	1,88
Annual Rate of Return	24,87%

Table 17. Performance Ratio Analysis of ETF Simulation

Performance Ratios	
Upside Potential Ratio	19,85
Sharpe Ratio	,18
Annualized Sharpe Ratio	,61
Sortino Ratio	,25
Fouse Ratio	,01
Calmar Ratio	,01
Sterling Ratio	0
Portfolio Net Profit as % of Largest loss	6160,24%
Portfolio Net Profit as % of Max Trade Drawdown	6298,99%
Portfolio Net Profit as % of Max Portfolio Drawdown	187,61%
Select Net Profit as % of Largest loss	3812,58%
Select Net Profit as % of Max Trade Drawdown	3898,46%
Select Net Profit as % of Max Strategy Drawdown	116,11%
Adj Net Profit as % of Largest loss	5162,2%
Adj Net Profit as % of Max Trade Drawdown	5278,47%
Adj Net Profit as % of Max Strategy Drawdown	157,22%

Figure 17. Equity Curve Detailed With Drawdown Analysis of ETF Simulation

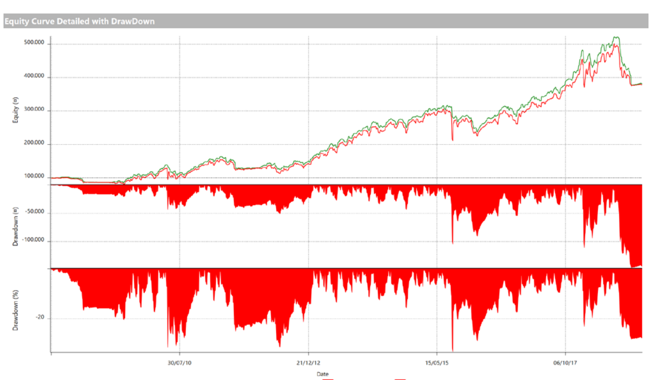


Table 18. Annual Rolling Period Analysis of ETF Simulation

Annual Rolling Period Analysis					
Period	**Net Profit**	**% Profit**	**Profit Factor**	**# Trades**	**Percent Profitable**
Today - 2019	2.251,56 ¤	,6%	2,59	6	50%
2018 - 2019	(30.807,10 ¤)	(7,5%)	(,35)	52	30,77%
2017 - 2019	81.078,25 ¤	27,13%	3,33	62	61,29%
2016 - 2019	103.451,28 ¤	37,42%	2,81	78	56,41%
2015 - 2019	97.159,06 ¤	34,36%	2,07	93	50,54%
2014 - 2019	133.435,07 ¤	54,14%	2,89	106	58,49%
2013 - 2019	237.627,56 ¤	167%	5,77	106	69,81%
2012 - 2019	250.248,15 ¤	192,99%	5,97	112	66,07%
2011 - 2019	240.540,48 ¤	172,58%	4,5	142	53,52%
2010 - 2019	267.303,29 ¤	237,36%	5,46	150	66%
2009 - 2019	292.883,95 ¤	336,51%	5,94	151	66,89%
2008 - 2019	279.920,12 ¤	279,92%	1,84	160	63,12%

Table 19. Annual Period Analysis of ETF Simulation

Annual Period Analysis					
Period	**Net Profit**	**% Profit**	**Profit Factor**	**# Trades**	**Percent Profitable**
2019	2.251,56 ¤	,6%	2,59	6	50%
2018	(33.058,66 ¤)	(8,05%)	(,29)	48	29,17%
2017	111.885,35 ¤	37,44%	7,63	54	77,78%
2016	22.373,04 ¤	8,09%	1,72	53	66,04%
2015	(6.292,23 ¤)	(2,23%)	(,7)	39	48,72%
2014	36.276,01 ¤	14,72%	5,33	44	70,45%
2013	104.192,49 ¤	73,22%	307,29	40	97,5%
2012	12.620,59 ¤	9,73%	2,65	40	65%
2011	(9.707,67 ¤)	(6,96%)	(,3)	37	16,22%
2010	26.762,81 ¤	23,76%	7,52	44	79,55%
2009	25.580,66 ¤	29,39%	21,91	36	80,56%
2008	(12.963,82 ¤)	(12,96%)	-0	10	0%

As can be seen from the results, the performance achieved, net of commissions, was in line with previous tests. In some ways, they were even better.

Comparison With Theoretical Strategies

Compared to the simulation of the strategy with size in percentage, these are the main differences:

- Profit factor decreased from 6.18 to 4.85.
- Yield increased from 191% to 280%.
- Maximum drawdown increased from 26.5% to 33.1%.
- Drawdown close to close increased from 11.8% to 16.1%.
- Average annual yield increased from 24% to 24.9%.

Considering the commissional impact present in the simulation with the ETF that instead is not present in the one with the indices, we can affirm that the results of the simulation with ETF do not differ too much from those made with the indices.

Comparing the results of the simulation with the ETF with the trend of the benchmark (Dow Jones U.S. Total Market). Figure 18 shows the Dow Jones U.S. Total Market from 2008 to the present day.

Figure 18. Dow Jones U.S. Total Market Price Action From 2008 to 2019 Based on Monthly Timeframe

Comparison With the Benchmark

Table 20 shows the results of the comparison from 2008 to 2019.

Table 20. Comparison Between ETF Simulation and djus.x Index Taken as a Benchmark

2008–2010	Simulated ETF	Benchmark (djus.x)
Return	203.44%	95%
Max Drawdown	33.74%	54%

The results are very much in favour of the strategy applied to the ETFs. In fact, it can be seen that there has been a doubling of yields in the face of a significant reduction in losses. All this considering that 57.6% of the initial capital would have been sufficient to implement the strategy and thus would have allowed liquidity to be reinvested in other strategies or other asset classes.

Comparison With the Best Actively Managed Fund

And finally, we complete the research with a comparison against the best equity fund present since January 1, 2008, until today. We are talking about the Franklin U.S. Opportunities W accumulation of which we can see in Figure 19.

Figure 19. Franklin U.S. Opportunities W Fund From 2008 to 2019

Let's now see the comparison in the usual comparative table.

Table 21. Comparison Between ETF Simulation and Franklin U.S. Opportunity W Fund Taken as Benchmark

2008–2010	Simulated ETF	Franklin U.S. Opportunities Acc
Return	203.44%	229%
Max Drawdown	33.74%	-38,8%

As we can see, the results are quite similar, both in terms of the final performance and the maximum drawdown sustained. The fund has achieved a slightly higher yield in the face of a substantial increase in risk. We should bear in mind that this fund used for comparison is the one that has offered the highest return since 2008, out of a total of 91 similar funds for management style.

The Current Portfolio

As of the time this was written (March 6, 2019), the strategy has the following portfolio:

Table 22. Current Portfolio Based on the Strategy With Percentage Size of 5%

Instrument	Position	Open P/L	Net Profit	Risk Capital	Equity
				Strategy 1	
XLV	+219	¤3,410.…	¤6,312.…	¤911.69	¤9,722.29
XLK	Flat	¤0.00	¤9,087.…	¤0.00	¤9,087.45
VGT	Flat	¤0.00	¤13,00…	¤0.00	¤13,003.79
XLE	Flat	¤0.00	¤-3,311…	¤0.00	¤-3,311.98
XLY	Flat	¤0.00	¤10,16…	¤0.00	¤10,164.96
XLU	+447	¤1,669.…	¤-308.22	¤1,306.94	¤1,360.97
IBB	Flat	¤0.00	¤6,507.…	¤0.00	¤6,507.72
FDN	Flat	¤0.00	¤18,91…	¤0.00	¤18,912.95
ITA	Flat	¤0.00	¤12,07…	¤0.00	¤12,079.00
IHI	+83	¤-516.43	¤12,46…	¤1,061.00	¤11,949.61
KRE	Flat	¤0.00	¤1,759.…	¤0.00	¤1,759.22
IGV	+92	¤-677.91	¤11,56…	¤1,061.18	¤10,887.82
KBE	Flat	¤0.00	¤1,534.…	¤0.00	¤1,534.64
XOP	Flat	¤0.00	¤-3,776…	¤0.00	¤-3,776.72
SKYY	Flat	¤0.00	¤5,746.…	¤0.00	¤5,746.83
HACK	Flat	¤0.00	¤5,890.…	¤0.00	¤5,890.82
IYG	Flat	¤0.00	¤9,454.…	¤0.00	¤9,454.62
VOX	Flat	¤0.00	¤2,932.…	¤0.00	¤2,932.67
SOXX	Flat	¤0.00	¤13,71…	¤0.00	¤13,714.58
ITB	Flat	¤0.00	¤2,116.…	¤0.00	¤2,116.51
IHF	Flat	¤0.00	¤10,45…	¤0.00	¤10,456.91
PBS	Flat	¤0.00	¤6,482.…	¤0.00	¤6,482.33
PHO	+580	¤461.97	¤3,288.…	¤1,043.13	¤3,750.05

Beyond the U.S. Stock Market

In conclusion, the strategy has been tested with the same parameters in other markets as well. Specifically:

- Global Sectoral versus Global Equity
- European Sectoral vs. European Equity
- Sectoral Italian vs. Equity Italian
- American stock picking against S&P 500

The simulations made on these markets are not the subject of this research, so I will not go into the merits, but have all produced better results than the respective benchmarks.

Conclusion

The research carried out has achieved the two intended objectives:

- Create a strategy that beats the American market and does what more than 97% of active funds fail to do.
- Create a strategy that can contain the losses of the stock market that are the main cause of worry for investors and what keeps them away from this type of investment.

The results obtained by the strategy have been more than satisfactory, as:

- It has achieved higher returns than the stock market over a time horizon of almost 20 years.
- It contained losses compared to the American stock market, especially during the two financial crises of 2000 and 2008.
- It did better than the best active fund on the American stock market in terms of both risk and return.
- It has enabled better results to be achieved in terms of both risk and return by using less capital than the original capital.
- It has produced results in line with expectations even with a simulation with ETF net of commissions.

This strategy can be set up and implemented as of tomorrow by:

- Small private investors who want to invest their capital independently, following an approach that can produce higher returns and lower risks than the American stock market.
- Financial advisors who want to use a long-term investment strategy to invest the capital of their clients.
- Active fund managers who want to have a management style that really can beat the market.
- Companies that produce ETFs that want to create an ETF composed of ETFs (today we are beginning to see several) that exploit a mechanical methodology are able to do better than the market.

I don't know if these professional and private figures will one day use the strategy presented in this paper, but I'm sure of one thing: I started applying it in real life with my capital today!

27.02 Day Cycle Model

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Abstract

The 27.02 Day Cycle combines the dominant role of the number Pi (3.14 ...) with the anomalistic orbital period of the earth (365.2596 days).[1] The significance of the 27.02 Day Cycle has been verified on the basis of the highly capitalized and broadly diversified S&P-500-Index. As the investigation shows, a synchronicity[4] between the 27.02 Day Cycle and the price development on the financial markets seems to exist. It is about the phenomenon of temporally correlated events that are not linked by a causal relationship but are perceived to be interconnected or interrelated. The observations made and the theory of synchronicity were the basis for further investigations and the development of the 27.02 Day Cycle Model. For the determination of the calendar calibration, a market correction with more then -5% must occasionally coincide with the 27.02 Day Cycle change. The first calibration point was set on 16 February 2004. The model is based on three basic algorithms: 27.02 Day Cycle Core, 27.02 Day Cycle Core Target, and 27.02 Day Cycle Core Error. Constructive corrections allow, after the finalization of a 27.02 Day Cycle Core formation, the determination of the Cycle Time Diameter. On this basis, the total cycle can then be calculated using the circular formula D x Pi. This algorithm can be used during the boom phase to determine the time forecast for new significant highs. The transition from the boom phase to the bust phase is usually indicated by a 27.02 Day Cycle Error. Since the calibration of the 27.02 Day Cycle with the calendar in 2004, there has been no recalibration to date. The 27.02 Day Cycle is to a certain extent only the carrier frequency for the development of emancipated cycles without a fixed time corset. The presented investigations led to the question of whether a natural 27.02 Day Cycle exists in nature. The significance of the 27.02 Day Cycle becomes clear when investigating the solar magnetic field and thus, with the character of the solar dynamo. As the results of astrophysics research show, the synodic solar rotation period plays a dominant role with 27.02 (+/- 0.02) days (see References). Surprisingly, the product of the solar rotation period and the anomalistic period of the earth brings to light the Pi formula. The result 3.141546 ... is consistent with the natural constant Pi = 3.141592 ... up to and including the fourth digit after the decimal point. There is also a mathematical relation between the Fine Structure Constant 137[5] and the 27.02 Day Cycle. From the reciprocal of 27.02 in the square, the FSC can be derived theoretically. The presented research also opens up a series of interesting questions for mathematics and astrophysics.

Introduction

Background

The search for natural cyclical patterns, which may have an impact on the financial markets, has long been a fascination for analysts. Especially interesting is the moon with its moon phases. Therefore, it is no wonder that there are already countless studies and publications on this phenomenon.

This was the motivation to look for more patterns. For this purpose, formulas consisting of mathematical constants and natural cycles were designed and tested. In this experiment was the following formula, which links the number Pi with the anomalistic orbit period[1] of the earth.

$$\frac{\text{Pi}^2 \text{ x } 1000}{365.2596 \text{ Days}} = 27.020793 = 27.02 \text{ Day Cycle}^{2)}$$

The significance of this formula has been verified on the basis of the highly capitalized and broadly diversified S&P 500 Index. The calendar calibration[3] of the 27.02 Day Cycle took place on the basis of dominant price highs, which coincided exactly with the 27.02 Day Cycle. Important high points often fall on the last day of the cycle. As the investigation shows, a synchronicity[4] between the 27.02 Day Cycle and the price development on the financial markets seems to exist. Of particular importance is in each case the last and first cycle day—the pulse beat of the 27.02 DC. Figure 1a – 1e shows typical examples.

Figure 1a. S&P 500 – History 2007

Figure 1b. S&P 500 — History 2009

Figure 1c. S&P 500 — History 2011

Figure 1d. S&P 500 — History 2016

Figure 1e. S&P 500 — Part of 2018–2019

The following research results focus solely on the highly capitalized and diversified S&P 500.

The Phenomenon of Synchronicity

Synchronicity[4] describes temporally coincident occurrences of acausal events. The phenomenon of synchronicity was described by quantum physicist and Nobel laureate Wolfgang Pauli and depth psychologist C.G. Jung and intensively researched. See more under the DISCUSSION section.

Methodology

27.02 Day Cycle Model

The observations made and the theory of synchronicity were the basis for further investigations and the development of the 27.02 Day Cycle Model.

27.02 Day Cycle—Calendar Calibration

The calibration of the 27.02 DC[3] with the calendar was made on the basis of the data collected between 2004 and 2007. The first calibration point was set on 16 February 2004. For the further date calculation, a cycle duration of 27.020793 days was used according to the algorithm. To confirm the correctness of the calibration over and over again, occasionally larger corrections must be observed with the cycle change. Table 1 shows only the corrections with more than -5%, which have arisen with the cycle change. Until today, no recalibration took place.

Table 1. 27.02 Day Cycle — Calender Calibration With S&P 500

27.02 Day Cycle - last Cycle Day *			27.02 Day Cycle - new Cycle *		
Date	Closing	Dev. from the Top (%)	Date	Market correction	Hint
15.02.04	1.145,81	1,00%	16.02.04	-5,9%	
27.02.05	1.211,37	0,00%	28.02.05	-6,1%	
05.05.06	1.325,76	0,00%	06.05.06	-6,9%	
26.02.07	1.449,37	0,70%	27.02.07	-5,9%	China Crash
12.07.07	1.547,70	0,35%	13.07.07	-9,2%	
01.10.07	1.547,04	1,20%	02.10.07	-56,0%	Financial Crisis
28.10.07	1.535,28	0,90%	29.10.07	-9,2%	
02.01.09	931,80	0,30%	03.01.09	-27,6%	First 27.02 DC Core after the Baisse
03.05.10	1.202,26	1,20%	04.05.10	-16,0%	Flash Crash
10.07.11	1.343,80	0,70%	11.07.11	-17,8%	
02.05.12	1.402,31	0,25%	03.05.12	-9,0%	
14.09.12	1.465,77	0,00%	17.09.12	-7,7%	
04.12.14	2.071,92	0,17%	05.12.14	-5,0%	
23.06.16	2.113,32	0,00%	24.06.16	-5,5%	Brexit Decision
02.12.18	2.760,17	1,00%	03.12.18	-16,0%	Trade dispute: USA / China

Average	0,52%	-13,6%

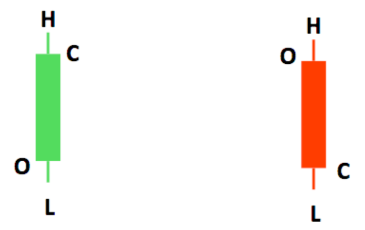
* If the beginning or the end of a 27.02 DC coincides with a weekend or a public holiday, it is calculated on the basis of the latest or next available price data. For the 27.02 DC graduation this is the last closing price, for the 27.02 DC start the first opening course afterwards.

27.02 Day Cycle Candle

The basis for all further considerations is the 27.02 Day Cycle calibrated with the calendar. To simplify the explanation, the price development of a 27.02 Day Cycle is shown as a candle (see Figure 2).

Figure 2. 27.02 Day Cycle Candle

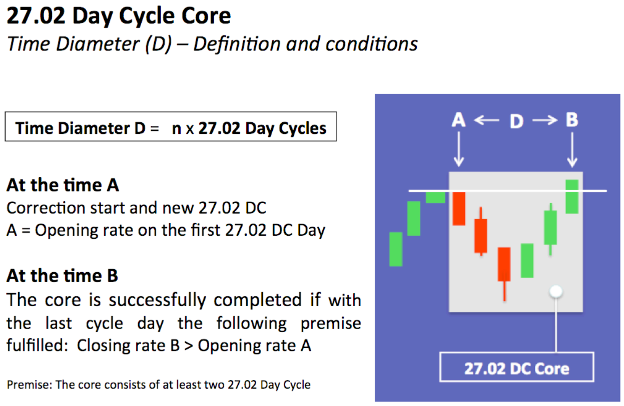
O	Opening rate on the first Cycle Day
H	Intracycle the highest daily closing rate
L	Intracycle the lowest daily closing rate
C	Closing rate on the last Cycle Day



27.02 Day Cycle Core

The foundation of the 27.02 Day Cycle Model consists of the 27.02 DC Core. The formation starts with the beginning of a correction (Time A) and is completed when the closing price at Time B the first time is greater than at Time A. The time in between is the Time Diameter D. Figure 3 describes Model Algorithm 1.

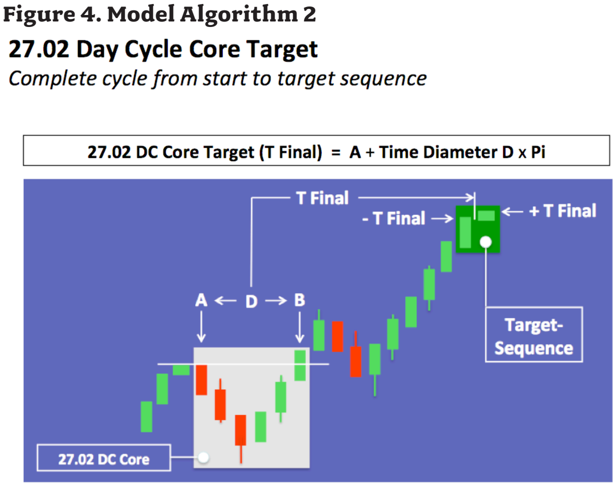
Figure 3. Model Algorithm 1



27.02 Day Cycle Core Target

After completion of the 27.02 DC Core the total cycle and thus the 27.02 DC Core Target can be calculated with the help of the formula: D x Pi. The calculated date T Final is between two 27.02 DC Endpoints. The cycle high point is usually reached by -T Final or (+ T Final).[3] Figure 4 describes Model Algorithm 2.

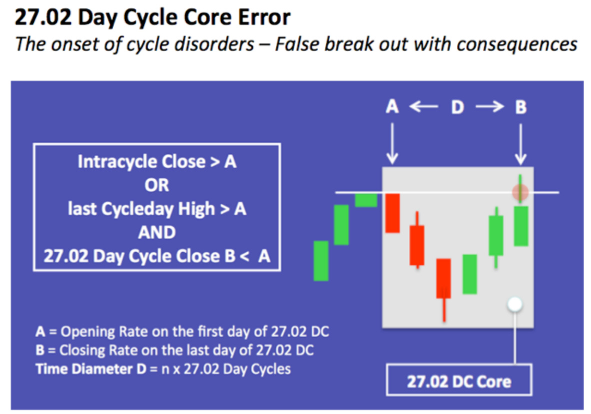
Figure 4. Model Algorithm 2



27.02 Day Cycle Core Error

The 27.02 DCM not only provides the time forecast for significant highs in the boom phase but also typically triggers a signal in time before the start of a bust phase. The basis for this is the 27.02 DC Core Error. Figure 5 shows the principle of Model Algorithm 3.

Figure 5. Model Algorithm 3



Results

Complete Cycles From Core Start to Target-Sequence

The following two practical examples reflect model algorithm 1, 27.02 Day Cycle Core, and 2, 27.02 Day Cycle Core Target, described earlier. The example below shows and explains Cycle 0506. The origin and the development until the end of the cycle are shown in Figures 6a and 6b.

Figure 6a. Cycle 0506 — Core History

At the Time A = May 6, 2006
First trading day in the new 27.02 DC
Open = 1.325.76 Points

At the Time B = October 13, 2006
Last trading day in the current 27.02 DC
Close = 1.365.62 Points

Figure 6b. Cycle 0506 — From Core Start to Target-Sequence

-T Final	Target (T)	+T Final
04.09.2007	23.09.2007	01.10.2007
1.489.42	1.525.75	1.547.04

Each cycle will be named after the month and year of the 27.02 DC Core opening. For example, the chart shows the development of Cycle 0506. Point A is May 6, 2006, and the first 27.02 DC day. This was the beginning of the correction and thus, the starting point for the 27.02 DC Core. After six 27.02 DC, the 27.02 DC Core was completed on October 13, 2006. Now the premise B > A was fulfilled. The time between point A and B corresponds to the Time Diameter D.
After completing the 27.02 DC Core, the total cycle size up to the target sequence can now be calculated using the formula D x Pi. The high point of Cycle 0506 was reached with + T Final on October 1, 2007. Cycle 0506 was the last intact cycle before the onset of the financial crisis.

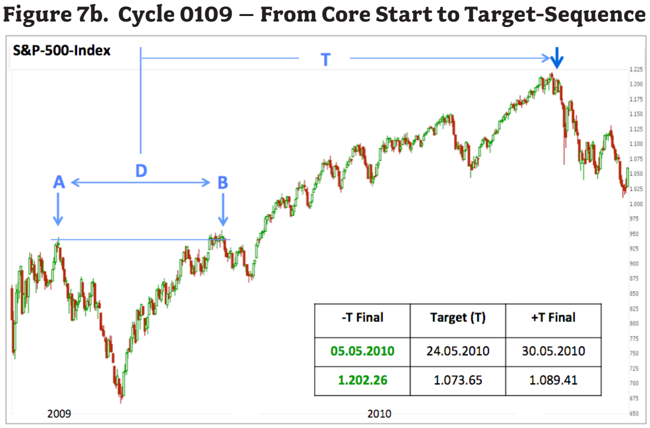
The second example (Figures 7a and 7b) shows the origin and development Cycle 0109.

Figure 7a. Cycle 0109 — Core History

At the Time A = January 3, 2009
First trading day in the new 27.02 DC
Open = 929.17 Points

At the Time B = June 12, 2009
Last Trading day in the current 27.02 DC
Close = 946.21 Points

Figure 7b. Cycle 0109 — From Core Start to Target-Sequence



The successful finalization of the core formation of Cycle 0109 was also the signal for the end of the bust phase and the beginning of a new bull market.

S&P 500 Statistics — All Complete Cycles Since 2003

Since the beginning of the investigations in 2003, a total of 23 Cycle patterns have been observed in the S&P 500 Index to date—from the 27.02 DC Core start to the cycle completion by the 27.02 DC Core Target. The data available now confirms the high correlation between the completion of 27.02 DC Core and the achievement of significant highs by the 27.02 DC Core Target Sequence.

Table 2 gives an overview and statistics for all cycles from core start to target-sequence. Since 2003, 23 cycles have been observed in the S&P 500.0

Cycle Error When Changing From Boom Phase to Bust Phase

The following two practical examples reflect the model algorithm 3, 27.02 Day Cycle Core Error, described earlier. Figures 8a and 8b (overview and detail view) show the outbreak of the last financial crisis from the perspective of the 27.02 Day Cycle Model.

Figure 8a. 27.02 Day Cycle Error in 2007 — Overview

Figure 8b. 27.02 Day Cycle Error in 2007 — Detail View

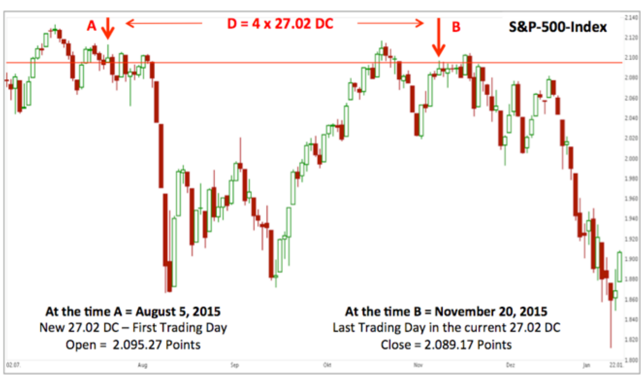
Figures 9a and 9b (overview and detail view) show the first of two 27.02 Day Cycle Errors in 2015.

Figure 9a. 27.02 Day Cycle Error in 2015 — Overview

Table 2. S&P 500 Statistics — All Complete Cycles Since 2003

27.02 Day Cycle Core							Target Sequenz						Further Price
Cycle	A Open	Date	Core Low	B Close	Date	n x 27.02 DC´s	- T Final	Target (T) = A + D x Pi	+ T Final	Cycle Top	Rise in (%)	Distance to the Top (%)	Right after the end of the Cycle Top
0603	1.011	17.06.03	965	1.021	06.09.03	3	1.146	1.145	1.121	15.02.04	12,2%	1,0%	-7,3%
0204	1.146	16.02.04	1.063	1.173	11.11.04	10	1.286	1.252	1.246	01.06.06	9,6%	3,0%	-4,8%
0205	1.211	28.02.05	1.143	1.222	12.07.05	5	1.296	1.308	1.326	05.05.06	8,5%	0,0%	-7,3%
0506	1.326	06.05.06	1.224	1.366	14.10.06	6	1.489	1.526	1.547	01.10.07	13,3%	1,1%	-51,5%
0207	1.449	27.02.07	1.374	1.484	22.04.07	2	1.497	1.407	1.489	08.08.07	0,9%	0,0%	-5,8%
0109	929	03.01.09	677	946	13.06.09	6	1.202	1.074	1.089	03.05.10	27,1%	1,2%	-14,9%
0711	1.343	11.07.11	1.099	1.371	09.03.12	9	1.710	1.691	1.633	04.08.13	24,7%	0,0%	-4,7%
0512	1.402	03.05.12	1.278	1.418	18.08.12	4	1.557	1.560	1.542	04.04.13	10,0%	-	11 Days = before rising again
0912	1.465	15.09.12	1.353	1.503	27.01.13	5	1.752	1.771	1.781	20.11.13	18,5%	-	18 Days = before rising again
0513	1.658	16.05.13	1.573	1.710	04.08.13	3	1.819	1.828	1.797	23.01.14	6,9%	1,1%	-4,8%
0813	1.708	05.08.13	1.630	1.752	24.10.13	3	1.865	1.831	1.881	02.05.14	7,4%	-	13 Days = before rising again
1113	1.784	21.11.13	1.775	1.819	13.01.14	2	1.881	1.878	1.920	29.05.14	5,6%	-	directly rising further
0114	1.821	14.01.14	1.742	1.878	08.03.14	2	1.960	1.960	1.984	22.07.14	5,6%	0,2%	-3,9%
0314	1.878	09.03.14	1.816	1.881	02.05.14	2	1.972	1.988	1.986	23.08.14	5,7%	1,1%	-6,3%
0714	1.985	23.07.14	1.910	1.986	14.09.14	2	2.059	2.021	2.030	31.12.14	3,7%	1,6%	-2,7%
0914	1.986	15.09.14	1.862	2.032	07.11.14	2	2.110	2.105	2.108	23.02.15	3,8%	0,4%	-3,3%
0515	2.121	16.05.15	1.829	2.173	20.07.16	16	2.665	2.681	2.775	21.02.19	27,7%	pending	pending
0816	2.178	17.08.16	2.085	2.192	02.12.16	4	2.410	2.473	2.478	02.08.17	13,0%	0,0%	-2,1%
0317	2.379	21.03.17	2.329	2.391	13.05.17	2	2.446	2.477	2.497	25.09.17	4,4%	0,5%	directly rising further
0617	2.426	10.06.17	2.410	2.478	02.08.17	2	2.579	2.602	2.676	16.12.17	8,0%	-	9 Days = before rising again
0817	2.476	03.08.17	2.426	2.497	25.09.17	2	2.786	2.803	2.581	17.01.18	12,2%	2,5%	7 Days > before the correction
0118	2.799	13.01.18	2.588	2.802	20.07.18	7	Target Sequenz: -T Final 02.08.19 to +T Final 29.08.19						
0918	2.897	13.09.18	----- pending -----										
Summary							**7**	**4**	**10**		**11%**	**0,9%**	**-9,2%**

Figure 9b. 27.2 Day Cycle Error in 2015 — Detail View



In 2015, the boom phase was about to end. This can also be seen in the development of U.S. junk bonds (HYG Index). From mid-2015 to early 2016, the share price fell sharply again. In this market phase, a 27.02 DC Core Error was triggered twice. Both correction waves were relatively moderate, with minus 10.8% and 12.5%, respectively. The intervention of monetary policy prevented a big crash in 2015.

Since 2003, three errors have occurred—Table 3 shows the details.

Table 3. 27.02 Day Cycle Core Error Since 2003

27.02 Day Cycle Core Error							Trigger Point		Further Price	
Cycle	A Open	Date	Core High *	B Close	Date	n * 27.02 DC´s	Distance to the Top (%)	Number of trading days before the crash start	Correctur (%)	Duration
0707	1.547,68	13.07.07	1.549,02	1.547,04	01.10.07	3	1,2%	6	-56,0%	17 Months
0515	2.121,30	16.05.15	2.128,28	2.093,32	04.08.15	3	0,4%	4	-10,8%	3 Weeks
0815	2.095,27	05.08.15	2.109,79	2.089,17	20.11.15	4	0,6%	6	-12,5%	11 Weeks

* according to algorithm rules - see model algorithm 3

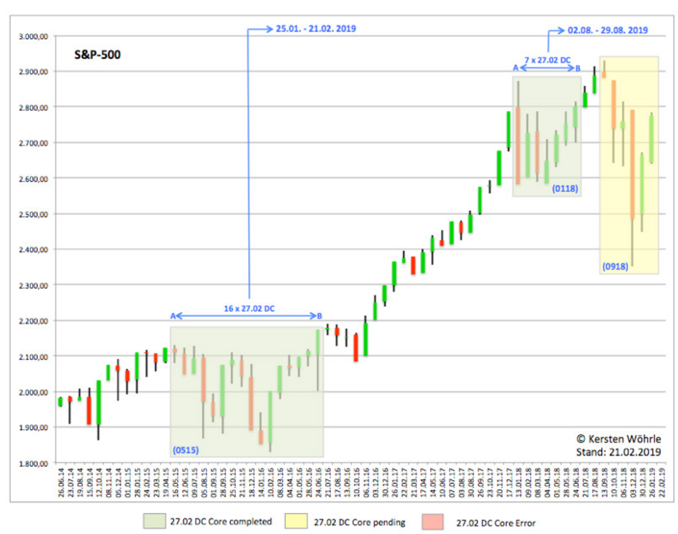
Current Status and Outlook

Due to great interest, the current status since 2017 is published on the VTAD homepage with every 27.02 Day Cycle completion: www.vtad.de.

This makes the 27.02 Day Cycle Model forecast transparent to all interested parties and comparable to the actual development.

The course of the S&P 500 Index is shown in 27.02 Day Cycle mode. Figure 10 shows the development from 2014 until the handover date of this paper.

Figure 10. S&P 500 in 27.02 Day Cycle Mode — Status as of February 2019



Discussion

The Mystery of Pi, Also With a View of Our Solar System

The presented investigations led to the question of whether a natural 27.02 Day Cycle exists in nature. The interest was focused on the sun. At the latest since the discovery of the sunspots, it is known that the sun also turns around its own axis (sun rotation period). The observed rotation period varies between the solar equator and poles from 24 to over 30 days. Rotation is affected by various factors (e.g., surface structure, sunspot activity). The significance of the 27.02 Day Cycle becomes clear when investigating the solar magnetic field and thus, with the character of the solar dynamo. As the results of astrophysics research show, the synodic solar rotation period plays a dominant role with 27.02 (+/- 0.02) days (see References).

The product of the solar rotation period and the anomalistic period of the earth[1] brings the following formula to light:

$$\pi = \sqrt{\frac{\text{Solar rotation period x anomalistic period of the earth}}{1000}} \qquad 2)$$

$$\pi = \sqrt{\frac{\text{27.02 Days x 365,2596 Days}}{1000}}$$

The result 3.141546 … is consistent with the natural constant Pi = 3.141592 … up to and including the fourth digit after the decimal point!

The Cosmic Number 137 and the 27.02 Day Cycle

The fine-structure constant,[5] so to speak, unites three fundamental physical theories: electron theory, quantum theory and relativity theory. It's just a number, because the dimensions cancel each other out.

e Charge of the electron
h Planck's constant
c Speed of Light

$$\frac{2\pi e^2}{hc}$$

From this symbol bundle, the number 0.00729 derives. For better handling, the reciprocal value 137 is used. In this matter, a new and interesting mathematical finding[6] is the relationship between the fine-structure constant 137, Pi, and the anomalistic orbital period[1] of the earth.

$$\text{FSC} = \frac{1}{\left(\frac{\pi^2 \times 10^3}{365.2596}\right)^2} \times 10^5 = \frac{1}{\text{27.02 Day Cycle}^2} \times 10^5 = \mathbf{136.963}$$

Table 4 gives an overview of all theoretical values for fine-structure constant.[7]

Table 4. FSC Values

Date	Author(s)	Expression	Value
1914	Lewis and Adams	$8\pi(8\pi^5/15)^{1/3}$	137.348
1928	Perles	$[2\pi(\pi-1)]^{-1} m_p/m_e$	136.455 7
1930	Eddington	$(16^2-16)/2+16+1$	137 (exactly)
1931	Beck et al.	$T_0=-(2/\alpha-l)$ °C	137.075
1970	Wyler	$(8\pi^4/9)(2^4 5!/\pi^5)^{1/4}$	137.036 082
1972	Aspden and Eagles	$108\pi(8/1843)^{1/6}$	137.035 915
1973	Cohen and Taylor	Review value	137.036 04

The number 137 is one of the great last secrets of physics. This fact has already led to noteworthy quotations among leading scientists.

Quantum physicist and Nobel laureate Wolfgang Pauli:

"If God allowed me to ask a question, it would be: why the number 137?"

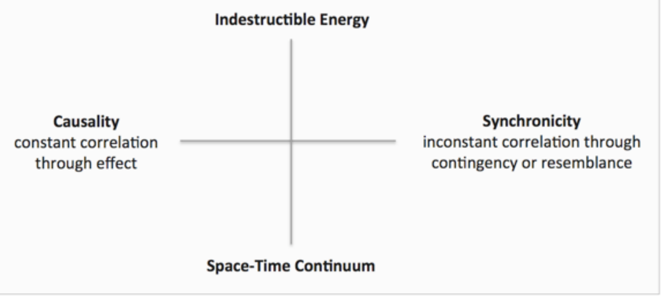
Physicist Laurence Eaves, professor at the University of Nottingham:

"I think the number 137 would be the one you'd signal to the aliens to indicate that we have some measure of mastery over our planet and understand quantum mechanics. The aliens would know the number as well, especially if they developed advanced sciences."

The Phenomenon of Synchronicity

Synchronicity describes temporally coincident occurrences of acausal events. The phenomenon of synchronicity was described by quantum physicist and Nobel laureate Wolfgang Pauli and depth psychologist C.G. Jung and intensively researched (see References). In their collaboration, they sought explanations to reveal hidden symmetries or an inner harmony of nature. The Pauli principle reveals such symmetry in the atomic world. It says that, for example, in an atom, no two electrons may occupy the exact same state. The exclusion principle or Pauli principle is not based on any forces acting between the particles, but rather an excellent example of an "acausal" linkage. Or to put it more generally: It is about the phenomenon of temporally correlated events that are not linked by a causal relationship but are perceived to be interconnected or interrelated. Figure 11 illustrates the Jung–Pauli concept.

Figure 11. Jung–Pauli Concept



Summary

The research presented in this paper leads to a whole bundle of new questions. As could be shown, there is a relation of the 27.02 Day Cycle to the anomalistic period of the earth, the natural constant Pi, and the fine-structure constant 137. In addition, we have seen that exists in our central star, the Sun, a natural 27.02 day cycle. Therefore, it is almost no surprise that the 27.02 Day Cycle has to leave its mark on human and collective behavior. This is likely to be the most pronounced, where many people are acting together in a large and balanced market.

High points in the S&P 500 serve the 27.02 Day Cycle as bases for anchorage with the calendar. To what extent the phenomenon of synchronicity plays a role, or rather only the statistical probability finds its expression, remains open. Using computer-aided models, current research finds more and more evidence of the results of Wolfgang Pauli and C.G. Jung regarding the phenomenon of synchronicity. Crucial here, however, is that the 27.02 Day Cycle is to a certain extent only the carrier frequency for the development of emancipated cycles.

Conclusion

27.02 Day Cycle Model

The 27.02 Day Cycle combines the dominant role of the number Pi with the anomalistic orbital period of the earth with 365.2596 days.[1]

The 27.02 Day Cycle is the basic cycle for cycles with time of origin and period develop emancipated—a cycle without a fixed time corset.

The 27.02 Day Cycle Model is a market-phase indicator that distinguishes between two states: boom phase or bust phase.

Constructive corrections allow, after the finalization of a core formation (27.02 DC Core), the time forecast for new major tops.

The transition from the boom to the bust phase is usually indicated by a 27.02 Day Cycle Error.

During the bust phase, no 27.02 Day Cycle Core will be formed—lower highs are followed by new lows.

Since the calibration of the 27.02 Day Cycle with the calendar in 2004, there has been no recalibration to date.

Future Work

To allow a further assessment of the cycle model, the evaluation on the basis of further key indices is required in the next few years.

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Notes

1. The anomalistic period is the time of a planet between the repeated passage of the pericenter. It is the actual orbit period of a planet. The planetary orbit period results from the third Kepler law.
2. The formula was first published in the Smart Investor 08-2015.
3. If the beginning or the end of a 27.02 DC coincides with a weekend or a public holiday, it is calculated on the basis of the latest or next available price data. For the 27.02 DC graduation, this is the last closing price, for the 27.02 DC start the first opening course afterwards.
4. Synchronicity are events to describe temporally coincident occurrences of acausal events. The phenomenon of synchronicity was described by quantum physicist and Nobel laureate Wolfgang Pauli and depth psychologist C.G. Jung intensively researched (for more details see References).
5. It was discovered in 1916 by Arnold Sommerfeld.
6. First publication in the MFTA Paper.
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Abbreviations

27.02 DC = 27.02 Day Cycle

27.02 DCM = 27.02 Day Cycle Model

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The Irreversibility Indicator IREV

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Abstract

(Ir)reversibility is a characteristic of time series that, despite its close relationship with trends, is currently not captured by any of the common technical indicators. In this article, an indicator that is able to do so is constructed, based on a reflection of how irreversibility should be (re)defined in trading—the IREV. It calculates the oriented divergence between the probability distributions of the market price read forwards and backwards based on ordinal permutations (e.g., (1,2,3) or (3,2,1) for an increasing or decreasing price, respectively). The IREV is qualitatively discussed for an instructive price development and quantitatively tested for the DAX members in 2018. The results indicate that it gives precise signals and obtains significantly better average cumulated returns than the MACD, as an example for a common indicator.

Introduction

Technical indicators are used to capture different aspects of a given historical price development to forecast its future continuation. Usually, one indicator covers mainly one such aspect, and dependent on which aspect this is, indicators can be classified into several categories. A common, somewhat detailed such categorization is presented in Table 1.

The technical analysis of price developments is, of course, closely related to academic time series analysis, as each price development is a time series. The aspects covered by the different indicator categories are therefore usually reflected by the concepts discussed in the latter domain, if by another name (column 3). However, in that domain, further important concepts exist that so far have not been covered by corresponding indicators, often because they have been developed in a completely different discipline than financial analysis. Such concepts can serve technical analysis with additional novel information.

One such concept, primarily analyzed in physics, is *reversibility*. Simply put, it describes *changes in the state of the object represented by the time series that could always revert without the object (or its environment) experiencing a permanent change* (loosely based on [3], p. 59). Other changes in state are called irreversible.

By this definition, one can intuitively grasp the value that the consideration of irreversibility could add to current technical analysis: What is a trend other than an (until further events) irreversible change in the state of the asset? This means that indicators of irreversibility should carry information on trends, if indirectly. As they are based on price dynamics (i.e., toing and froing) instead of changes in the mean price, they do not belong to the category of trend indicators but give standalone, so far unutilized information in the above sense.

In this article, a first member to the category of irreversibility indicators is developed based on recent research on time series, the IREV. Due to its particular calculation, it gives not only information on the current trend but also on the current momentum.

Construction of the IREV

Definition of irreversibility in technical analysis

To construct an indicator for the irreversibility of a price development, at first a formal definition of this concept is needed. As a basis, the inverse definition of reversibility as used in time series analysis can be considered. There, a stochastic process is called reversible if it produces the series $\{x_{t+1},\ldots,x_{t+n}\}$ at all points in time t and for any length n with the same probability as the series $\{x_{t-1},\ldots,x_{t-n}\}$; if X is stationary, this probability is identical to the one of the reverse series $\{x_{t+n},\ldots,x_{t+1}\}$ ([4]).

For technical analysis, however, this strict definition cannot

Table 1. Categories of Technical Indicators (loosely based on [1, 2])

Input	Category	Related concepts of time series analysis	Aspect covered	Examples
Only price	Trend	Expectation, (Non)stationarity	Change of mean	Moving Average (MA), Average Directional Index (ADX)
	Volatility	Standard deviation, Heteroskedasticity	Spread around mean	Bollinger Bands (BB), Average True Range (ATR)
	Momentum	Auto-Regressivity	Influence of previous values	Relative Strength Index (RSI), Stochastic Oscillator
Additional data	Volume	Reliability	Substance of changes (investors)	Ease Of Movement (EMV), On-Balance Volume (OBV)
	Market	Reliability	Substance of changes (firms)	Advance-Decline-Line (ADL), McClellan Oscillator

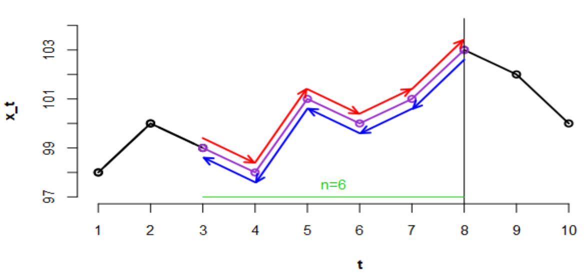
be directly employed. This has five reasons, which necessitate five corresponding adaptations:

1. Reversibility in the above definition is a qualitative concept, meaning that X is either reversible or not (i.e., irreversible), but we are rather interested in the *degree* of irreversibility—that is, we need a quantitative concept.
2. The above definition is concerned with X as a whole, but we do not (only) want to know whether or how much a price development is irreversible from start to end—since that would give us only a single piece of information—but to analyze certain windows and to investigate if and how irreversibility changes in their progress.
3. Correspondingly, we do not need to assume that the above property holds for series of any length n but choose a certain value for n for all windows.
4. Also—and this is the most important adaptation—we neither require that the above property holds for all points in time t nor stationarity, but we still want to compare the probability of the series $\{x_{t+1},\dots,x_{t+n}\}$ with that of its reverse $\{x_{t+n},\dots,x_{t+1}\}$ for each t.
5. This is not possible, however, as we do not know X and, thus, cannot predict its further development at t. Therefore, we do not look into the future but rather into the past and compare $\{x_{t-n+1},\dots,x_t\}$ with $\{x_t,\dots,x_{t-n+1}\}$ instead of the above-mentioned series (the former are obtained by replacing t with $t-n$ in the latter).

Summarizing, the concept of irreversibility is defined for technical analysis as follows: *A price development is the more irreversible at a point in time t with regard to a window of length n (period), the greater the divergence is between the (future-projected) probability distributions* $\mathcal{P}^{\rightarrow}\{x_{t-n+1},\dots,x_t\}$ *and* $\mathcal{P}^{\leftarrow}\{x_t,\dots,x_{t-n+1}\}$.

Figure 1 illustrates this definition. Here, at t=8 a price development of length n=6, {99, 98, 101, 100, 101, 103} (red), is compared to its (fictitious) reverse, i.e., {103, 101, 100, 101, 98, 99} (blue). The divergence of the corresponding probability distributions in t gives the irreversibility (as a side note, the exact probabilities are irrelevant for our purposes).

Figure 1. Illustration of the Presented Definition of Irreversibility



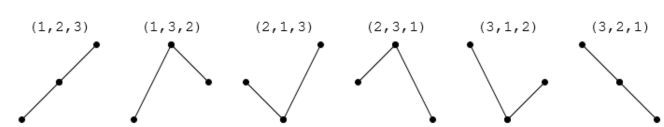
Discretization of the price development

Unfortunately, the obtained definition of irreversibility cannot be operationalized so far because neither the forward probability distribution $\mathcal{P}^{\rightarrow}$ nor its backward counterpart $\mathcal{P}^{\leftarrow}$ is known; thus, these distributions have to be estimated by the given data first.

Market prices represent continuous data, as they can take not only a few distinct values but virtually infinitely many in-between. The estimation of such distributions is difficult; it would require advanced concepts such as kernel density estimation (see, e.g., [5]), with the efforts exceeding the benefits. In such situations, one usually decides to discretize the data before their analysis, that is to map each data point to one of only a few groups. A variety of methods exist for this purpose; research on reversibility has often employed clustering algorithms or approaches based on graph theory (e.g., [6]).

However, we choose another method, which has been introduced in this kind of research just recently ([7, 8]) and can thus be regarded state-of-the-art: ordinal permutations ([9]). An ordinal permutation of dimension is an array (i.e., a vector) of the numbers 1 to d that reflects the order of a sequence of numbers of length d, where represents the lowest number and the highest. For the simplest case of $d = 2$ ($d = 1$ would be trivial) and a sequence x_1,x_2 of this length, there logically exist only two such permutations, namely (1,2) if $x_1 < x_2$ and (2,1) if $x_1 > x_2$ (ties as for $x_1 = x_2$ can be resolved randomly). For d =3, there already exist six permutations (these are illustrated in Figure 2), for an arbitrary value of d there are $d! = d\,(d-1)\cdots 1$. One would generally prefer a higher value for d in order to capture as much information as possible; however, as we will see later on, this choice is strongly limited by a quickly increasing necessary minimum value of n.

Figure 2. The Six Ordinal Permutations for Dimension d=3



The method of ordinal permutations offers a range of advantages; these are nicely pointed out by Zanin et al. ([8], p. 2): First, only one parameter has to be chosen, with the choice, as mentioned, being strongly restricted at that. Second, it can be applied locally (i.e., it allows the analysis of temporary fluctuations). Third, it does not depend on scaling. Fourth, it converges more "quickly" (that is, with shorter time series) than, for example, graph-based methods. In technical analysis, there also exists a fifth advantage, which should be explicated here: A series of permutations, as we will analyze below, strongly reminds us of formation analysis. The famous "Head and Shoulders" pattern, for example, could be represented by the (reversible!) permutation series {(1,2,3), (2,13), (3,1,2), (3,2,1)} (see again Figure 2). This relationship surely would deserve closer inspection, but this is out of the present work's scope.

Discretizing the price development (or, more precisely, its current window) by ordinal permutations is very simple. To do so, the window is just partitioned into several overlapping sections of length d – there always exist exactly

$$m = n - (d - 1) \tag{1}$$

of these –, which then are replaced by the corresponding permutation. Let us consider again the red forward movement {99, 98, 101, 100, 101, 103} of Figure 1 and choose d=2 for illustration. 99 is greater than 98, so the discretized series starts with permutation (2,1). Then, 98 has to be compared to 101, which leads to permutation (1,2), and so on. The resulting permutation series is {(2,1), (1,2), (2,1), (1,2), (1,2)} of length m=6-(2-1)=5. To obtain its counterpart for the blue backward movement, it simply has to be read backwards.

It is noteworthy that by the application of ordinal permutations, levels in the price development disappear (e.g., {98, 101} and {101, 103} are both mapped to (1,2)) so that the permutation series is much closer to being stationary than the price series.

Estimation of the probability distributions

After discretization, it principally is simple to estimate the probability distributions $\mathcal{P}^{\rightarrow}$ and $\mathcal{P}^{\leftarrow}$. These now are based on the permutation series rather than the price series, so they can be considered multinomial distributions of order *d*!(as there are this many possible results), and all that remains is to determine the respective result probabilities.

The obvious approach to estimate these would be to use the corresponding relative frequencies $\frac{k}{m}$: When in the above example the permutation (1,2) appears *k*=3 times in the forward movement of *m*=5 permutations, $\frac{3}{5}$= 60% looks like a reasonable estimation of its probability. However, let us consider another example window in which occurs a pure downward movement, i.e., the permutation series [(2,1), (2,1), (2,1), (2,1), (2,1)]. (1,2) would then be assigned a probability of 0% by the relative-frequency method, but one cannot reasonably assume that a permutation has been factually *impossible* just because it did not appear. Due to this (and a few other problems), a better estimator is needed.

It has been shown that $\frac{(k+2)}{(m+4)}$ is such a better estimator for *d*=2 (i.e., a binomial distribution), if this, strictly speaking, is true only for intervals ([10]). The idea behind it can, somewhat heuristically, be generalized to other values of *d*, too:

$$\mathcal{P}^{\{\rightarrow;\leftarrow\}}(y) = \frac{k_y^{\{\rightarrow;\leftarrow\}} + 2}{m + 2 \cdot d!} \qquad (2)$$

for each permutation *y*, where $k_y^{\rightarrow}$ bzw. $k_y^{\leftarrow}$ again count the absolute frequency of *y* among the *m* permutations of the forward and the backward series, respectively. For the above example, we now have $\mathcal{P}^{\rightarrow}((1,2)) = (3+2)/(5+4) = 5/9$ and $\mathcal{P}^{\rightarrow}((2,1)) = 1 - 5/9 = 4/9$; for $\mathcal{P}^{\leftarrow}$ it is the other way around. Note that the difference between 5/9 and 3/5 is rather small.

As we now have obtained a practicable method for estimating $\mathcal{P}^{\rightarrow}$ and $\mathcal{P}^{\leftarrow}$ dependent on *d* (and *n*), the choice of this parameter should be commented. A higher choice overproportionally increases the number of probabilities that have to be estimated (*d!*–1; the last probability is then obtained by summing up to 1) and decreases the number of data points available for this purpose (*n*–(*d*–1)). Thus, high values of *d*, which would be preferable as mentioned earlier, require a large *n; n*≥(*d*+1)([8]) can be seen as a rule of thumb. This shows why in practice, only *d*=2 (n≥6), *d*=3 (*n*≥24), and *d*=4 (n≥120) are meaningful. These values *n* for can be interpreted as short-term, mid-term, and long-term analyses, respectively, so that there is clear advice on which *d* to choose for each term.

Calculation of the divergence

Having estimated $\mathcal{P}^{\rightarrow}$ and $\mathcal{P}^{\leftarrow}$, we can now quantify their difference. As measure for such a difference, one usually employs the Kullback-Leibler divergence KLD, which for two arbitrary probability distributions $\mathcal{P}^1$ and $\mathcal{P}^2$ is defined as

$$\mathrm{KLD}(\mathcal{P}^1, \mathcal{P}^2) = \sum_y \mathcal{P}^1(y) \cdot \log_2\left(\frac{\mathcal{P}^1(y)}{\mathcal{P}^2(y)}\right). \qquad (3)$$

It reflects, loosely speaking, how much additional information $\mathcal{P}^2$ contains when one already knows $\mathcal{P}^1$. However, it has two important disadvantages: For one thing, it is not commutative [i.e., $KLD(\mathcal{P}^1,\mathcal{P}^2) \neq KLD(\mathcal{P}^2,\mathcal{P}^1)$], and there is no reason in our context to lay more focus on $\mathcal{P}^{\rightarrow}$ than on $\mathcal{P}^{\leftarrow}$ or vice versa. For another thing, the KLD has no finite maximum, which makes its interpretation difficult. Both disadvantages can be overcome by using the Jensen-Shannon divergence JSD instead, which is based on the KLD. It is calculated as

$$\mathrm{JSD}(\mathcal{P}^1, \mathcal{P}^2) = 1/2 \cdot \mathrm{KLD}(\mathcal{P}^1, \mathcal{M}) + 1/2 \cdot \mathrm{KLD}(\mathcal{P}^2, \mathcal{M}), \qquad (4)$$

where $M = \frac{1}{2} \cdot P^1 + \frac{1}{2} \cdot P^2$ is the mixture distribution of $\mathcal{P}^1$ and $\mathcal{P}^2$.

These formulas may look more complicated than they really are; their application to the continuous example from Figure 1 will demonstrate this. For this purpose, a scheme (Table 2) is introduced that can generally be used to calculate the JSD. The rows of this scheme have to be filled with all potential permutations for the chosen *d* first (including those that do not appear in the discretized series). Then, it is just calculated column by column. The JSD is finally given by the simple mean of the sums in the last two columns.

Table 2. Scheme for the Calculation of the JSD (applied to the example from Figure 1)

y	$k_y^{\rightarrow}$	$\mathcal{P}^{\rightarrow}(y)$	$k_y^{\leftarrow}$	$\mathcal{P}^{\leftarrow}(y)$	$\mathcal{M}(y)$	$\mathcal{P}^{\rightarrow}(y) \cdot \log_2\left(\frac{\mathcal{P}^{\rightarrow}(y)}{\mathcal{M}(y)}\right)$	$\mathcal{P}^{\leftarrow}(y) \cdot \log_2\left(\frac{\mathcal{P}^{\leftarrow}(y)}{\mathcal{M}(y)}\right)$
(1,2)	3	5/9	2	4/9	1/2	0.08445	-0.07552
(2,1)	2	4/9	3	5/9	1/2	-0.07552	0.08445
Σ	$5 = m$	1	5	1	1	0.008924	0.008924

Normalization to the IREV

So here, the JSD is $JSD = \frac{1}{2} \cdot 0.008924 + \frac{1}{2} \cdot 0.008924 = 0.008924$,[1] given in bits. In principle, one could already define this value as output of the IREV; it even had a quite intelligible interpretation similar to the one of the KLD (which would be without clear meaning in practical trading, though). However, it still exhibits an important limitation: It is not clear how large it should be regarded, due to the lack of a reference quantity. While JSDs always range between 0 and 1, so that one might be tempted to consider the above value rather small, it is not clear whether these theoretical boundaries can actually be met in our context (for example, because $\mathcal{P}^{\rightarrow}$ and $\mathcal{P}^{\leftarrow}$ are not independent of each other). Thus, the actual extremes have to be found, and the IREV has to be normalized accordingly as a last step.

The JSD takes its minimum value of 0 when $\mathcal{P}^1$ and $\mathcal{P}^2$ are identical. So the question is whether a price development exists for which $\mathcal{P}^{\rightarrow} = \mathcal{P}^{\leftarrow}$ This is the case at least for a stagnating development,[2] so that the lower bound of 0 can be regarded as sharp. The actual maximum value will inversely be reached for a monotonously increasing (or decreasing) price development, as $P^{\rightarrow}$ and $P^{\leftarrow}$ exhibit the largest difference for these cases. However, it can be shown with some effort (see Appendix A) that this maximum is not at 1 but only at

$$\mathrm{JSD}^{\max} = \frac{m+2}{m+2\cdot d!}\cdot \log_2\left(\frac{2\cdot m+4}{m+4}\right) + \frac{2}{m+2\cdot d!}\cdot \log_2\left(\frac{4}{m+4}\right) < 1. \quad (5)$$

[3]

For the usual parameter values of the IREV as given above, the following maximum values are obtained: JSD^{max} = 0.2358 for d=2 and n=6, JSD^{max}=0.4655 for d=3 and n=24, JSD^{max}=0.6442 for d=4 and n=120.

These results mean that the divergence between $P^{\rightarrow}$ and $P^{\leftarrow}$ needs to be dilated (but not shifted). The so-normalized JSD is a useful measure for the degree of irreversibility of a price movement. However, we want the IREV to additionally indicate the direction of this movement. For this purpose, we can simply compare the (forward-read) probability of the strictly ascending permutation (1,..., d), $\mathcal{P}^{\rightarrow}((1,..., d))$, with its counterpart for the strictly descending permutation (d,...,1), $\mathcal{P}^{\rightarrow}((1,..., d))$, by the sign function: the former (latter) being greater indicates an ascending (descending) price.[3]

Summarizing, the IREV can be defined as follows:

$$\mathrm{IREV}(d,n) = \mathrm{sgn}\left(\frac{\mathcal{P}^{\rightarrow}((1,\dots,d))}{\mathcal{P}^{\rightarrow}((d,\dots,1))} - 1\right)\cdot \frac{\mathrm{JSD}(\mathcal{P}^{\rightarrow},\mathcal{P}^{\leftarrow})}{\mathrm{JSD}^{\max}}. \quad (6)$$

As is a JSD^{max} itself and therefore measured in bits, this unit cancels out in (6). The IREV thus is unit-free; it gives the irreversibility in the current price window as share between 0 (0%) and 1 (100%) (upward movement) or 0 (0%) and -1 (-100%) (downward movement). Due to this, its values are comparable across different windows and even across different assets. For the continuous example, we have IREV = (+1) • 0.008924 0.2357955 = 0.03785 = 3.785%; the upward movement in Figure 1 can so be judged as almost completely reversible (no trend), and this is what indeed happens for $t \geq 9$.

The calculation of the IREV as pseudo-code can be found in Appendix B.

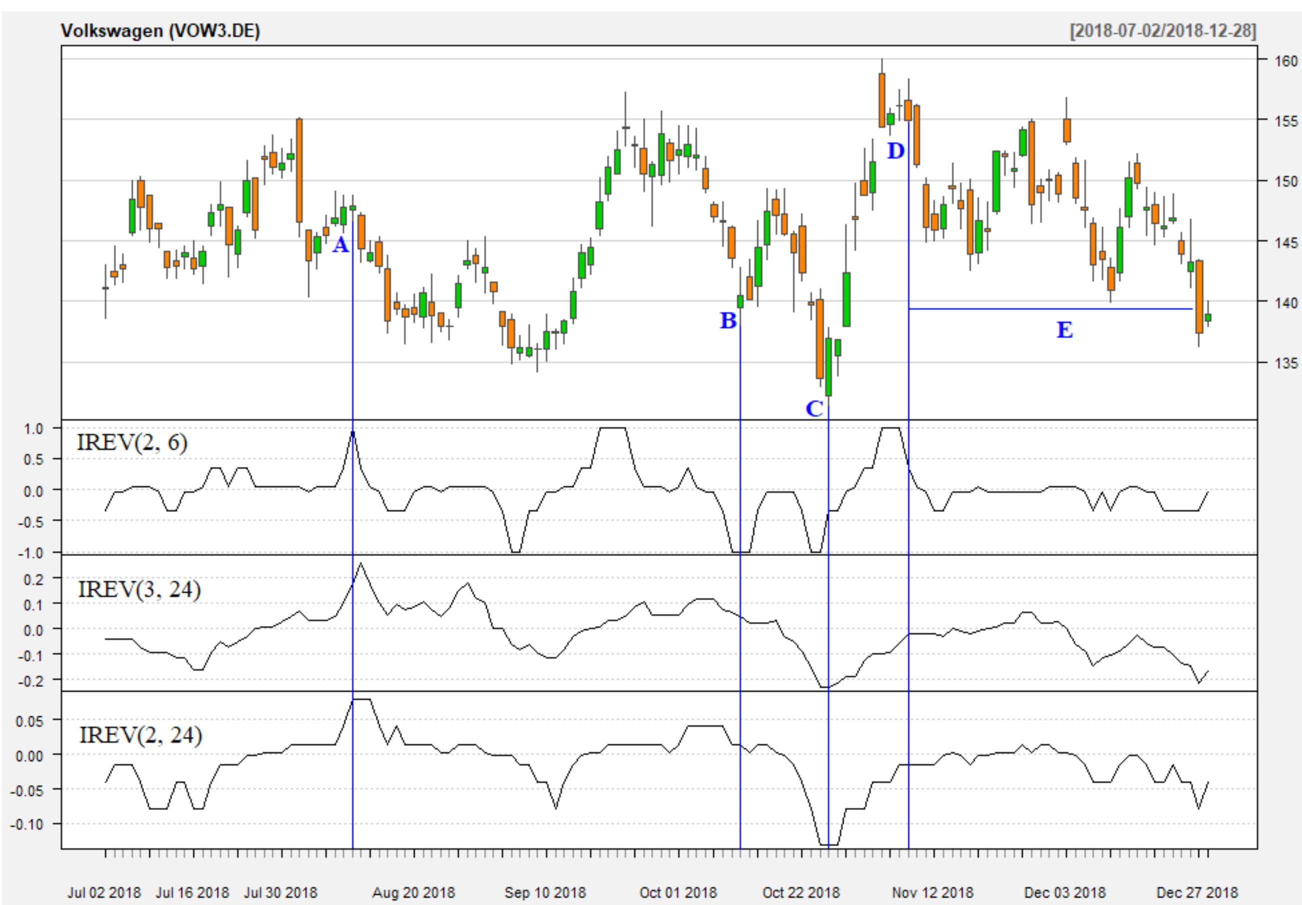
Application

The IREV can be applied and interpreted in several ways, but it is important to understand how it works and what its results mean, as one otherwise is prone to fallacies.

Meaning of period length *n* and dimension *d*

As indicated earlier, IREVs with essentially different parameter values represent different analyses, mostly with regard to the time range examined. Consider the instructive development of the Volkswagen stock market price (VOW3.DE) in the second half of 2018 and three indicators IREV(2, 6), IREV(3, 24), and IREV(2, 24), each based on close prices, for illustration (Figure 3). The interpretation of the IREV will be postponed to the next section; here, we are only concerned with the different parameter values.

Figure 3. Volkswagen Stock Market Price (VOW3.DE) in Second Half of 2018 With Three IREVs



Comparing the two "usual" IREVs, i.e., the short-term IREV (2, 6) and the mid-term IREV (3, 24), it can be seen that the latter gives many fewer signals than the former. This behavior is not surprising for larger period lengths and well-known from other indicators, such as moving averages. However, here, it is not so much due to stronger smoothing but rather due to different definitions of vertical movements (i.e., trends). This can be well observed at point B: As the short-term IREV sees only the last 6 trading days, which here have all been bearish, it is clear that it gives a signal. In contrast, the mid-term IREV looks back 24 trading days and therefore sees the whole "Double Top" formation right before B, not only its right part. There is no factual movement in this context, and so none is identified. At point C, when the IREV (2, 6) has already found a further short-term movement due to an in-between high, the formation's left part disappears for the IREV (3, 24), so that it now recognizes the former movement, too. However, it now should be interpreted as a mid-term one. This is a meaningful difference about which one has to be clear when choosing the period length n.

The dimension d rather is a technical parameter. As mentioned earlier, one would like to choose a large d in order to capture more information, but this choice is limited by the requirement of $n \geq (d+1)!$. If one intends to analyze wide price development windows (i.e., a large n) anyway, however, there is hardly a point in choosing a value for d smaller than necessary,[4] as it has been done here for the IREV (2, 24). Comparing it to the IREV (3, 24), no substantial differences can be recognized; rather, the former just reflects the latter but is less detailed due to less information carried.

Interpretation of the IREV

Attentive readers may have been surprised by Figure 3, to which we will refer here again, as it may seem that the IREVs were presented inversed there: We have defined them as indicators for the irreversibility of a price movement, but here, they almost perfectly identify its highs and lows (e.g., B and C) (i.e., points at which the trend reverts)!

The fallacy in this line of thinking is that "irreversibility" does not relate to a pair of a trend and a counter trend—as these trends can both be irreversible internally—but to the distinction between a trend and a horizontal movement. This can be well seen by the local high D: Before it, undoubtedly a trend has occurred, which has correctly been recognized. What follows is no counter trend (as for points B and C), however, but just irrelevant wriggling of the price (E); correspondingly, the IREV does not give a further signal.

As expected in the introduction to this work, the IREV can primarily be interpreted to indicate 1) the existence, 2) the so-far strength, and 3) the direction of a trend. With the trend becoming stronger, its absolute value increases until it reaches the maximum of 1. Of course, this is much more likely to happen for smaller period lengths than for larger ones, which explains the difference in scale between the IREV (2, 6) and the mid-term IREVs and will have to be taken into account when choosing a trading rule (discussed later). The IREV stays at its extreme value until it notices first indications of the trend's end. In the figure, this is exemplified by the long peak of the IREV (2, 6) right before point B.

This interpretation would more or less apply to other irreversibility indicators as well (if such existed). However, due to its calculation on the basis of ordinal permutations, the IREV can also be interpreted in the momentum context. A comparison with the Relative Strength Index (RSI), the arguably most famous indicator from the latter category, can illustrate the connection: Both indicators consider the upward and downward movements of the last days. The RSI determines their sums and averages but does not take into account their dynamics (i.e., the order of values); for the IREV, it is the other way around.[5] The consequences are exemplified by point A in the figure: Shortly before it (i.e., in the beginning of August 2018), the Volkswagen stock market price has fallen with an unusually high speed (presumably due to the release of a half-year report), which, however, does not enter the calculation of the IREV. Correspondingly, the trend that the IREV (3, 24) indicates here is not really justified (the signal of the IREV (2, 6) is due to a short upward movement right before A), while a RSI (6) (not shown in the figure) would correctly have kept calm here. On the other hand, the RSI (6) would have identified only two of the five IREV (2, 6)'s correct peaks—namely, the second and the fifth (point D); it misses the other three peaks (among them points B and C) because they average out.

Trading system and quantitative evaluation

After the qualitative analysis of the IREV, we will finally evaluate it quantitatively in a field test. For this purpose, a trading system is constructed that is solely based on the IREV and makes use of a very primitive trading rule:

Long if IREV $> \tau$, Short if IREV $< -\tau$, Unchanged position else

As indicated earlier, the threshold value τ should be chosen in dependence of n because the IREV reaches its maximum value of 1 the less likely the wider the window is for which it is calculated. A corresponding normalization can be to set $\tau = \frac{\alpha}{n}$, where α is a constant for all n; here, we choose α=2.4, which leads to τ=0.4 for the IREV (2, 6) and τ=0.1 for the IREV (3, 24). Figure 3 indicates that these are sensible threshold values.

Note that the presented trading system has been constructed only for demonstrative purposes and should not be applied to real trading. This is because the IREV, like any indicator, should never be used as the only source of information; rather, it should be combined with other indicators that capture further aspects of the price development (see Introduction).

As a benchmark for the IREV, the famous Moving Average Convergence/Divergence (MACD) indicator is employed; once in its standard configuration with periods of 12, 26, and 5 trading days, and once with halved values (i.e., 6, 13, and 5) to ensure a fair comparison with the IREV (2, 6). The MACD's standard trading rule (signal when the indicator crosses the signal line) is used for both versions.

The four indicators are calculated based on close prices, with the usual lag of one trading day, for the full year 2018 for all 30 members of the DAX (with the exception of LIN.DE due to raw data problems). For each of these assets, the cumulated annual return from using each indicator is measured by the common backtesting approach (see, e.g., [11]).

Table 3. Cumulated Annual Returns for the IREV in Comparison to the MACD

Symbol	IREV (2, 6)	IREV (3, 24)	MACD (12, 26, 9)	MACD (6, 13, 5)
1COV.DE	-0.04%	+64.76%	-11.18%	+73.41%
ADS.DE	+31.88%	-23.25%	+0.79%	-2.20%
ALV.DE	+5.85%	-26.37%	-2.99%	+4.88%
BAS.DE	+19.51%	+17.23%	+4.29%	+15.88%
BAYN.DE	+18.23%	-8.35%	-27.74%	+1.01%
BEI.DE	+2.20%	-3.79%	-13.22%	-13.47%
BMW.DE	+9.35%	+21.32%	-10.49%	-17.09%
CON.DE	+79.08%	+75.92%	-19.82%	-50.74%
DAI.DE	+0.26%	-5.25%	-28.45%	-16.85%
DB1.DE	-31.10%	-5.48%	-30.41%	-19.91%
DBK.DE	+83.30%	+83.26%	+15.75%	+47.08%
DPW.DE	+17.04%	+49.81%	+60.19%	-27.14%
DTE.DE	+15.89%	-1.30%	+9.92%	+8.53%
EOAN.DE	-3.13%	-12.32%	+1.46%	-10.14%
FME.DE	-28.79%	-4.23%	-28.71%	-15.51%
FRE.DE	+26.67%	-1.93%	-45.76%	-9.78%
HEI.DE	+17.02%	-2.13%	-4.65%	-5.38%
HEN3.DE	-15.55%	-15.43%	-5.05%	-9.02%
IFX.DE	+7.69%	-22.16%	-1.04%	+23.61%
LHA.DE	-35.52%	-41.47%	+5.29%	-20.34%
MRK.DE	+11.78%	+2.35%	-18.60%	-35.35%
MUV2.DE	-9.14%	-14.86%	-23.88%	-8.82%
RWE.DE	-41.17%	-40.65%	+35.88%	+46.36%
SAP.DE	+19.83%	+15.64%	-24.09%	-3.71%
SIE.DE	-6.99%	-18.49%	-23.25%	+46.43%
TKA.DE	+15.29%	-3.30%	-28.06%	+6.26%
VNA.DE	-25.98%	-1.39%	-1.91%	-19.58%
VOW3.DE	-46.35%	-5.83%	+6.25%	-1.44%
WDI.DE	-6.41%	+45.14%	-14.75%	-27.41%
Mean	+4.51%	+4.05%	-7.73%	-1.39%
# is +	17	9	9	10
# is best	14	5	5	5
LIN.DE has been excluded due to raw data problems				

The results are presented in Table 3. For their interpretation, one should keep in mind that the DAX fell by 18% in 2018, so that all indicators are subject to a bear market. So, it is not surprising that most of them (namely the mid-term IREV and both MACDs) exhibit positive returns for only about 1/3 of the assets. The actual surprise is that this number is as high as 58.6% (=17/29) for the IREV (2, 6), which demonstrates that it successfully captures short-term profits as it is supposed to. Correspondingly, it also obtains the highest average cumulated return of all four indicators: +4.51%. This might not be considered a large return in a year, but making profits at all in a bear market already is a noteworthy contribution. The mid-term IREV achieves a similar result (+4.05%), although this is rather due to a few very good trades than due to many good ones. In contrast, the two MACDs cannot compete with this performance: With both of them, traders would have lost money in 2018; for the traditional MACD (12, 26, 9), the average loss is as high as -7.73%.

The final decision on which indicator to use should arguably be based on the percentage of cases (assets) for which each indicator performs best (green cells in the table). Here, a clear winner can be declared: the short-term IREV. It achieves the highest return almost in each second case and, thus, three times as often as each of its competitors (14 vs. 5).

Conclusion

In this work, a first irreversibility indicator, the IREV, has been introduced. Even when employed as the only indicator in a trading system and using a very primitive trading rule, it exhibited promising results, greatly outperforming the common MACD indicator. Still, as next steps, its interplay with other indicators (as reasoned earlier, particularly the RSI seems to be a well-suited complement) should be investigated and, potentially integrating these, a more complex trading rule should be searched for.

Further research attention should also be given to the whole category of irreversibility indicators, as this concept still has not been exploited in practical trading despite its manifold possibilities of application. For example, another such indicator could be easily constructed by replacing the IREV's calculation by ordinal permutations (which also deserve separate investigation) with methods that are based on other criteria than the order of price changes. This can be inspired by the academic literature on time series analysis.

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Notes

1 The equality of both column sums in our example comes from d=2.
2 Due to above-mentioned random splitting of ties, this is true only in probability.
3 There may be some theoretical edge cases for which this simple rule fails.
4 One could only argue that $\mathcal{P}^{\rightarrow}$ and $\mathcal{P}^{\leftarrow}$ are more reliably estimated in that case.
5 Therefore, it can be assumed that the IREV and the RSI complement each other well.

Appendix A: Derivation of (5)

With regard to the actual maximum of JSD^{max} of $JSD(\mathcal{P}^{\rightarrow}, \mathcal{P}^{\leftarrow})$, it has already been pointed out that it will be reached exactly for a monotonously increasing price. Such a development is characterized by the appearance of only the strictly ascending permutation $(1,\ldots,d)$ in the forward movement and only the strictly descending permutation $(d,\ldots,1)$ in the backward movement. All other permutations appear with the same frequency in both movements – namely zero – so that they cancel out from the calculation due to $\mathcal{P}^{\rightarrow}(y) = \mathcal{P}^{\leftarrow}(y) = M(y)$ and, thus, $\log_2\left(\frac{\mathcal{P}^{\{\rightarrow,\leftarrow\}}(y)}{\mathcal{M}(y)}\right) = \log_2(1) = 0$. Consequently, the calculation scheme presented in Table 2 reduces to the one given in Table 4.

Table 4. Reduced Scheme From Table 2 for the Calculation of JSD^{max}

y	$k_y^{\rightarrow}$	$\mathcal{P}^{\rightarrow}(y)$	$k_y^{\leftarrow}$	$\mathcal{P}^{\leftarrow}(y)$	$\mathcal{M}(y)$	$\mathcal{P}^{\rightarrow}(y)\cdot\log_2\left(\frac{\mathcal{P}^{\rightarrow}(y)}{\mathcal{M}(y)}\right)$	$\mathcal{P}^{\leftarrow}(y)\cdot\log_2\left(\frac{\mathcal{P}^{\leftarrow}(y)}{\mathcal{M}(y)}\right)$
$(1,\ldots,d)$	m	$\frac{m+2}{m+2\cdot d!}$	0	$\frac{0+2}{m+2\cdot d!}$	$\frac{m/2+2}{m+2\cdot d!}$	A	B
$(d,\ldots,1)$	0	$\frac{0+2}{m+2\cdot d!}$	m	$\frac{m+2}{m+2\cdot d!}$	$\frac{m/2+2}{m+2\cdot d!}$	C	D
all others	0	$\frac{0+2}{m+2\cdot d!}$	0	$\frac{0+2}{m+2\cdot d!}$	$\frac{0+2}{m+2\cdot d!}$	0	0
Σ	m	1	m	1	1	$A+C$	$B+D$

Table 4: Reduced scheme from Table 2 for the calculation of JSD$^{\max}$.

Here, $A = \frac{m+2}{m+2\cdot d!}\cdot\log_2\left(\frac{\frac{m+2}{m+2\cdot d!}}{\frac{m/2+2}{m+2\cdot d!}}\right) = \frac{m+2}{m+2\cdot d!}\cdot\log_2\left(\frac{m+2}{m+2\cdot d!}\cdot\frac{m+2\cdot d!}{m/2+2}\right) = \frac{m+2}{m+2\cdot d!}\cdot\log_2\left(\frac{2\cdot m+4}{m+4}\right)$,

$B = \frac{0+2}{m+2\cdot d!}\cdot\log_2\left(\frac{\frac{0+2}{m+2\cdot d!}}{\frac{m/2+2}{m+2\cdot d!}}\right) = \frac{2}{m+2\cdot d!}\cdot\log_2\left(\frac{2}{m+2\cdot d!}\cdot\frac{m+2\cdot d!}{m/2+2}\right) = \frac{2}{m+2\cdot d!}\cdot\log_2\left(\frac{4}{m+4}\right)$, and, for symmetry reasons, $D = A$ and $C = B$. From this follows (5): $\mathrm{JSD}^{\max} = \frac{(A+C)+(B+D)}{2} = \frac{A+B+B+A}{2} = A + B = \frac{m+2}{m+2\cdot d!}\cdot\log_2\left(\frac{2\cdot m+4}{m+4}\right) + \frac{2}{m+2\cdot d!}\cdot\log_2\left(\frac{4}{m+4}\right)$.

Appendix B: Pseudo-Code for the IREV

```
IREV := function(d, n, x) {
 for (i:=n, i<=length(x), i:=i+1) {
  Pfw := estimateP(x, i-n+1, i, d);
  Pbw := estimateP(x, i, i-n+1, d);
  normJSD := JSD(Pfw, Pbw)/JSDmax(d, n);
  dir := sgn(Pfw[(1,…,d)]/Pfw[(d,…,1)]-1);
  irev[i] := dir*normJSD;
 }
 return irev;
}

estimateP := function(x, from, to, d) {
 dist := sgn(to-from)*(d-1);
 k := [0,…,0];
 for (i:=from, i<=to-dist, i:=i+1) {
  y := order(x[i,…,i+dist]);
  k[y] := k[y]+1;
 }
 m := n-(d-1);
 for (i:=1, i<=d!, i:=i+1) {
  P[y] := (k[y]+2)/(m+2*d!);
 }
 return P;
}
```

```
JSD := function(P1, P2) {
 M := (P1+P2)/2;
 jsd := (KLD(P1, M)+KLD(P2, M))/2;
 return jsd;
}

KLD := function(P1, P2) {
 kld := 0;
 for (i:=1, i<=length(P), i:=i+1) {
  kld := kld+P1[i]*log2(P1[i]/P2[i]);
 }
 return kld;
}

JSDmax := function(d, n) {
 m := n-(d-1);
 z1 := (m+2)/(m+2*d!);
 z2 := log2((2*m+4)/(m+4));
 z3 := 2/(m+2*d!);
 z4 := log2(4/(m+4));
 jsd := z1*z2+z3*z4;
 return jsd;
}
```

Cyclical Characteristics of Performance Indicators

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Abstract

This article is an extension to the MFTA paper titled "Linear Momentum and Performance Indicators", published in the 2019 *IFTA Journal*. The market performance indicators consist of two main groups: performance and integral performance indicators. The latter group leads prices and dissects the market's performance into six main elements: the market's momentum, pressure, strength, power, intensity and dynamic strength. This article enlightens about how those integral indicators are leading from a cyclical perspective. On another note, the integral power index is dissected thoroughly to show that its higher highs refer to weakness in prices and not strength! The reasoning behind this irregular behaviour leads to the introduction of a new concept in technical analysis—Market Energy.

Introduction

An Overview of the Market Integral Performance Indicators

The Integral Force Index (IFORI), alternatively the Linear Momentum Index (LMOMI)—LMOMI shows an adjustment of the price momentum concept in technical analysis. The contribution of volumes is a must to describe the price momentum.

The Integral Pressure Index (IPRI) measures the market integrated pressure. It relates the price momentum and volatility. A rising buying momentum is not necessarily accompanied by increasing buying pressure.

The Integral Strength Index (ISTRI) measures the market integrated strength, which analyzes the ability of bulls to resist the bears and vice versa. A high buying strength does not mean the bulls control the market; however, it indicates that the bears are unable to take over yet. The ISTRI relates the bulls and bears momentum to the magnitude of the session's shadow.

The following three indicators are the product of the price average velocity known as Wilder's momentum by the IFORI, IPRI and ISTRI, respectively.

The Integral Power Index (IPWRI) measures the market integrated power and differentiates it from the market momentum.

The Integral Intensity Index (IINTI) refers to how steep the moves of prices are. It can be thought of how fast the market is pressurised.

The Integral Dynamic Strength Index (IDSTRI) refers to the rate by which the market is showing strength.

In this article, the term *momentum* refers to linear momentum. The core of the formulas for those indicators is the following:

Price Average Velocity

$$v_{\text{avg}} = \left(\text{Price}_{\text{today}} - \text{Price}_{\text{yesterday}}\right)$$

IFORI (LMOMI)

$$\text{Momentum} = \text{Volume}_{\text{today}} x \left(\text{Price}_{\text{today}} - \text{Price}_{\text{yesterday}}\right)$$

$$\text{IPRI} = \text{Momentum}/\text{Range}$$

$$\text{ISTRI} = \text{Momentum}/\text{Shadow}$$

$$\text{IPWRI} = \text{Momentum } x \; v_{\text{avg}}$$

$$\text{IINTI} = \text{Momentum } x \; v_{\text{avg}}/\text{Range}$$

$$\text{IDSTRI} = \text{Momentum } x \; v_{\text{avg}}/\text{Shadow}$$

$$\text{Range Incremental } RI = 0.0001$$

$$\text{Strain Factor } SF = 1.01$$

$$\text{Range} = \text{H} - \text{L} + \text{RI}$$

$$\text{Real Body} = |\text{C} - \text{O}|$$

$$\text{Shadow} = (\text{SF } x \text{ Range}) - \text{Real Body}$$

To construct the indicators we add 14-day exponential moving averages to the formulas.

Mapping the Leading Indicators

The integral performance indicators (IPERIs) are leading to prices and leading each other, as shown in Figure 1.

Figure 1. The Lead Chart of Integral Performance Indicators

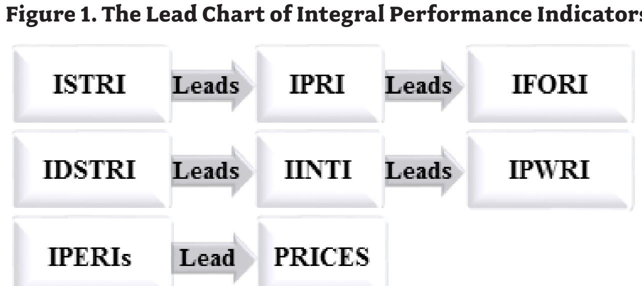


Table 1. Cyclical Lead of Bullish Integral Strength

PERIODS	Phase 1	Phase 2	Phase 3	Phase 4
PRICES			Prices rise	
IFORI (LMOMI)	0		Buying momentum rise	
IPRI	0	Buying pressure rise		
ISTRI	0			

Table 2. Cyclical Lead of Bullish Integral Dynamic Strength

PERIODS	Phase 1	Phase 2	Phase 3	Phase 4
PRICES			Prices rise	
IPWRI	0		Buying power rise	
IINTI	0	Buying intensity rise		
IDSTRI	0			

Table 3. Cyclical Lead of Bearish Integral Strength

PERIODS	Phase 1	Phase 2	Phase 3	Phase 4
PRICES			Prices decline	
IFORI (LMOMI)	0		Selling momentum rise	
IPRI	0	Selling pressure rise		
ISTRI	0			

Table 4. Cyclical Lead of Bearish Integral Dynamic Strength

PERIODS	Phase 1	Phase 2	Phase 3	Phase 4
PRICES			Prices decline	
IPWRI	0		Selling power rise	
IINTI	0	Selling intensity rise		
IDSTRI	0			

In Table 1, if the ISTRI is behaving differently than the IPRI and the IFORI during the same time interval of the first phase, then both will follow the ISTRI afterwards. To clarify, sometimes the ISTRI traces a higher high, showing a rise in buying integrated strength, and simultaneously the IPRI and IFORI trace a lower high, showing a decline in buying pressure and momentum, respectively. According to this situation, the buying pressure, momentum and prices should increase as shown in Table 1. In Table 2 and 4, the same behaviour exists among the IDSTRI, IINTI, IPWRI and prices while a variance among the duration of the phase is accepted.

Figure 2. The Cyclical Lead Among the IPRI, IFORI and Prices

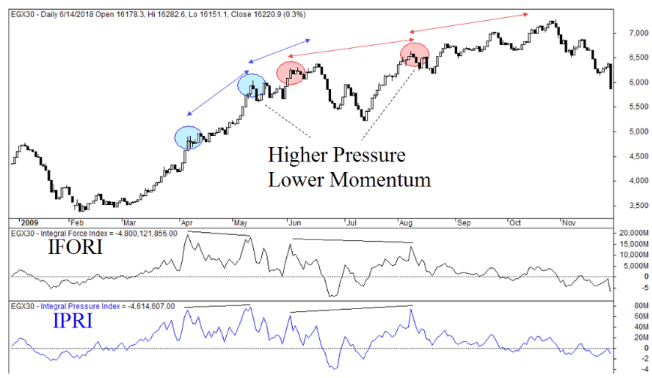
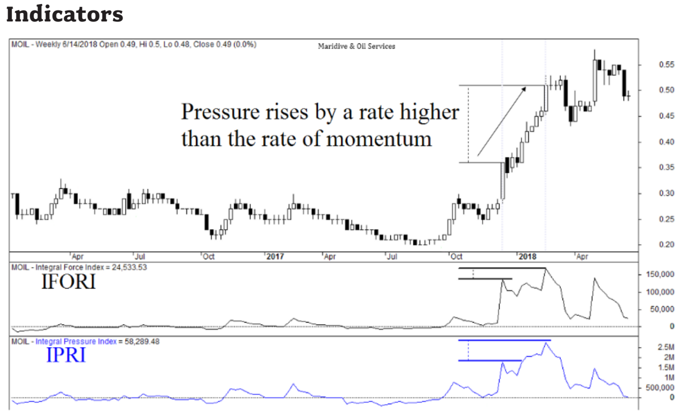


Figure 2 shows the rise of the EGX30 index in April 2009, accompanied by an increase in buying pressure and momentum. The index continued in an uptrend with a slight decline in buying momentum but with a rise in buying pressure in May. The surplus of the pressure over momentum paved the way to rising prices during June 2009. The indicators repeated the same behaviour from June to October. As a guideline, the negative divergence of the IFORI would fail when the IPRI does not show weakness in pressure.

Figure 3. Differences in Rising and Declining Rates of the Indicators



In Figure 3, the IFORI demonstrates a higher high at the beginning of 2018; moreover, the IPRI traces its second high at a greater rate. This excess of pressure refers to an existent buying momentum, which is represented by a higher peak that prices form in the following phase (after April 2018).

Figure 4. EGX: Orascom Telecom (OTMT.CA) — Daily Chart

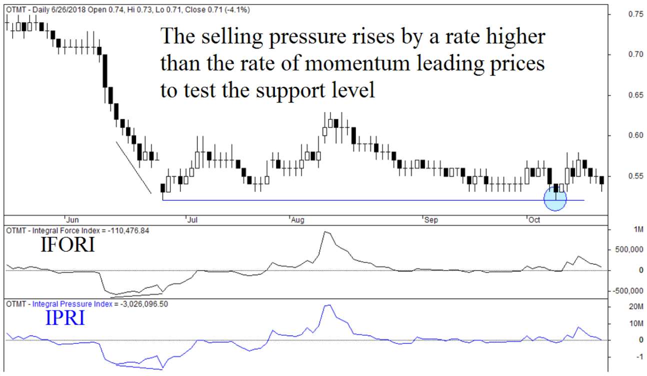
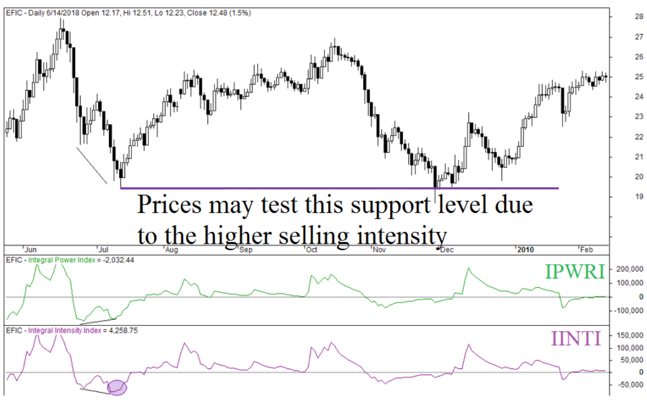


Figure 5. Testing the Support and Resistance



Figures 4 and 5 demonstrate the lead of the integral pressure to the momentum and the lead of the integral intensity to the integral power. The IINTI traced a lower low in July 2009, unlike the IPWRI. The difference in the declining rates is compensated for the subsequent extended phases by a decrease in selling power followed by a sharp decline in prices to test the support in November 2009.

Figure 6. The Lead Among Four Successive Phases

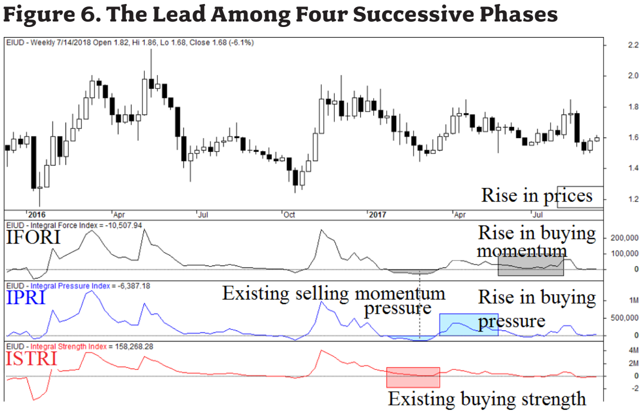
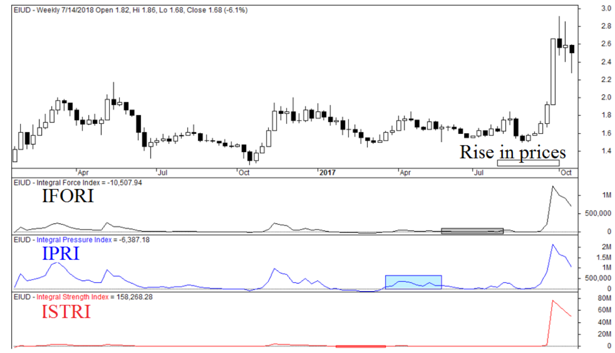


Figure 7. The Lead Among Four Successive Phases (cont'd)



In Figures 6 and 7, the first phase is for the first quarter of 2017. To define the phase's boundaries, find an agreement between the IFORI and IPRI and a simultaneous contradiction with the ISTRI. In this example, both the IFORI and IPRI agreed on selling performance (grey and blue dips), while the ISTRI showed an existing resistance of buyers concurrently. The increase in buying pressure and momentum at the subsequent phases is not necessarily to be traced by the indicators.

Figure 8 demonstrates a weekly chart of EGAS.CA. The stock was moving in a downtrend before changing its direction. During the reversal phase, the rate by which the IDSTRI increases is higher than the rates by which the IINTI and IPWRI prices increase. In Figure 9, the stock has moved in a rally with more intensity and power. In phase 3, the increase in power is showable by a rise in prices and not the IPWRI. However, the latter has traced a negative divergence instead. Such a divergence does not refer to weakness rather than a corrective action the IPWRI takes. The next section clarifies the unusual behaviour of the IPWRI.

Figure 8. The Lead by the Comparison of the Rising and Declining Rates

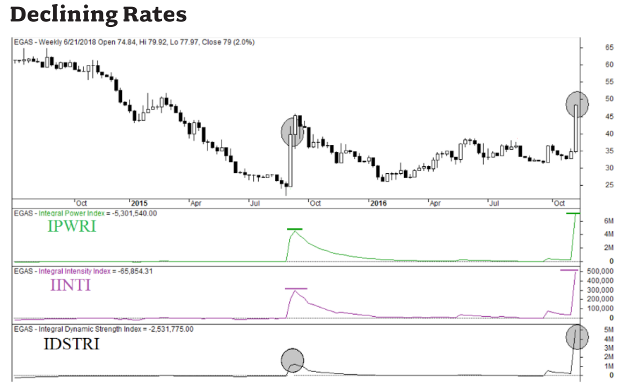
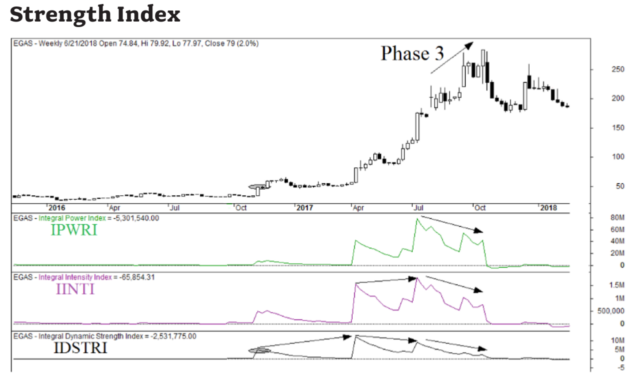


Figure 9. The Leading Effect of the Integral Dynamic Strength Index



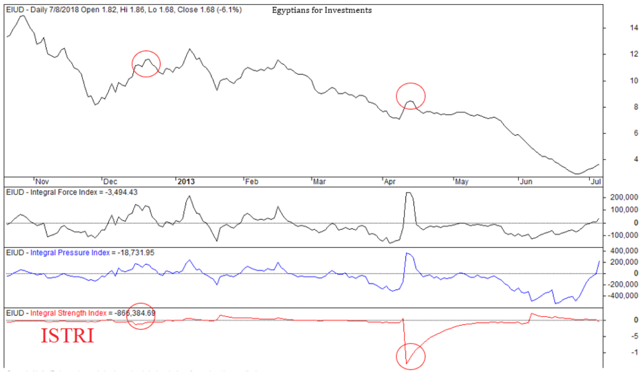


Figure 10. The Behaviour of the Integral Strength Index in Downtrends

Figure 10 illustrates the rise of the encircled selling strength. In December 2012 and April 2013, the stock experienced significant and minor corrections in a downtrend. During those corrections, the bulls were temporarily in control. The IFORI and the IPRI expressed this situation by a rise in buying momentum and pressure. Simultaneously, the ISTRI showed amplification in the selling strength to indicate the end of those corrections. The high selling strength hinders the buyers from taking over.

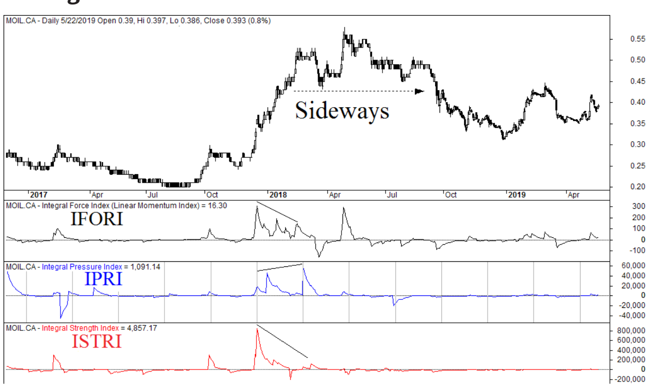


Figure 11. Integral Indexes of Pressure vs. Force and Strength

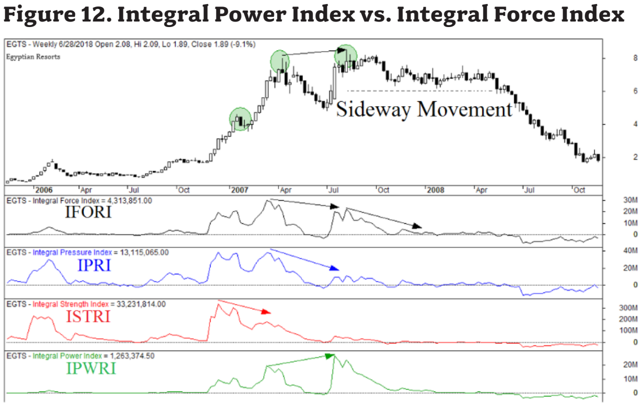


Figure 12. Integral Power Index vs. Integral Force Index

The integral performance indicators shed light on the tendency of prices to move sideways, giving a clue when the IPRI is not acting like the IFORI and the ISTRI. Besides, prices lean toward moving sideways when the IPWRI and the IFORI contradict each other. Figure 11 exhibits that the bulls have a low buying strength, which signifies the weak resistance of bulls against the selling pressure. The bulls have still been pressuring the bears with low momentum. Consequently, this would balance the demand with supply for the following phases. As a result, prices initiate a sideway pause for the uptrend. The IPWRI in Figures 12 and 13 traces a higher high, unlike the IFORI. Figure 14 shows a higher low for the IPWRI, unlike the IFORI in phase 1. By projecting the same time interval forward, the analyst should expect the price to bounce from 1800 to 2100 during phase 2.

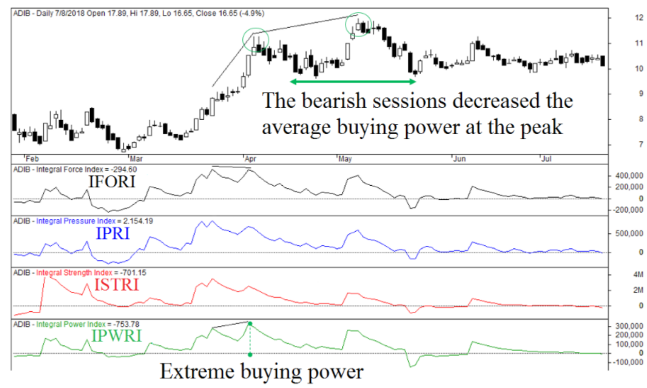


Figure 13. Special Behaviour of the Integral Power Index

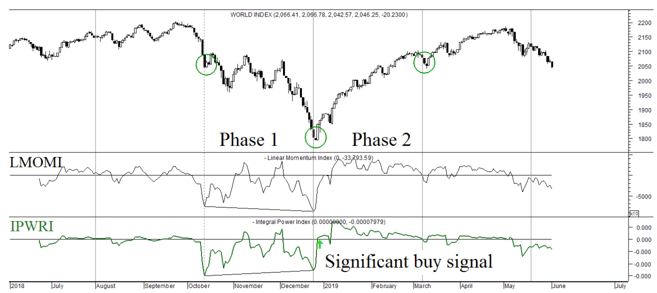


Figure 14. MSCI World Index (.WORLD) — Daily Chart

Not Every Higher High Is a Strength!

The IPWRI has a unique property that signifies *weakness in price movement when it develops a higher high*. This property is not typical for the momentum indicators in technical analysis. It arises from the relation between the price kinetic energy (integral power) and the price simple potential energy. Some people claim that the price behaviour in financial markets is affected by thermal, nuclear, or electromagnetic energies for such and such. Those speculations are not valid, as prices do not heat, radiate or carry the properties of an electron. However, the principles of kinetic and potential energies are applicable in the field of technical analysis as the price itself **MOVES.**

The kinetic energy (KE) is the energy a body owns by being in motion. The potential energy (PE) is the energy a body has due to its position relative to other objects or another level. The total energy (E) is the summation of those mechanical energies.

$$E = KE + PE$$

For isolated systems, the Law of Conservation of Energy states that the total energy in such systems remains constant over time.

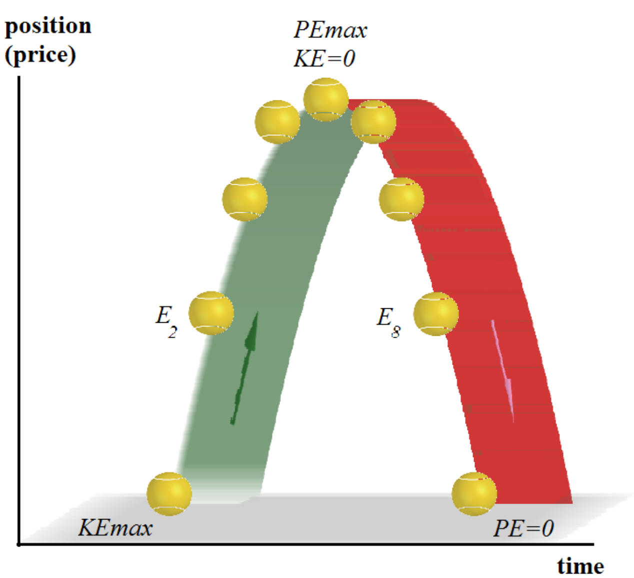
$$E_{in} = E_{out}$$

By analogy, energy is like *cash*. It is needed to perform some work "operations" through time. In a cash flow statement, the conservation between the cash inflows and outflows is a must. Any discrepancy in such conservation indicates a missing or inaccurate reflected item from the balance sheet. The same applies to the financial markets. The deviation from the law of conservation is what makes a difference between supply and demand driving a series of higher highs and higher lows during uptrends. However, the market may maintain the conservation in a later phase.

The movement of stocks is like consecutive rebounds of a ball. Figure 15 illustrates one rebound for a time interval of nine seconds (s). The ball hits the ground (turning point) at t = 1s to rebound with maximum velocity V_{max}. For the ball to perform such an action, it needs a kinetic energy equivalent to ($0.5\,mv^2$), where m is the mass of the ball. The formula of potential energy is (mgx) where x is the displacement from a reference level and g is the gravitational acceleration.

- At the ground level: $x = 0$; $v = v_{max}$
- At the peak: $x = x_{max}$; $v = 0$

Figure 15. Schematic Snapshot for the Tennis Ball Rebound Example



At the peak, the ball stops and loses its kinetic energy while gaining maximum potential energy due to its highest position relative to the ground. While falling downward, the ball gains back its kinetic energy and spends away its potential energy. At 2 seconds and 8 seconds, the ball is at the same level where the total energy is conserved $E_2 = E_8$. Briefly, Figure 15 shows that:

- For upside: KE declines and PE rises.
- For downside: KE rises and PE declines.

For the sake of simplification, the g of the price PE is equal to one, although it is calculable. *For this reason, it is called price simple potential energy.* "The price acts like a body constituted from building blocks of shares. A point that changes its position with time represents the price body." (El Sherbini, 2019). The mass of the price body is, therefore, its volume. Hence,

- *Price Kinetic Energy*=0.5 *Volume* $_{today}$. *(Price* $v_{avg})^2 = 0.5\,V.\,(P - P_y)^2$
- *Price Simple Potential Energy SPE = Volume* $_{today}$. *Price* $_{today}$ = *V.P*

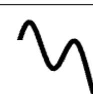
The previous formulas point out that the IPWR measures the price KE. Both indicators have the same shape despite the multiplication by 0.5.

- *Price Kinetic Energy (Integral Power)* = $EMA_{14}\,[0.5\,V.\,(P - P_y)^2]$
- *Price Simple Potential Energy SPE* = EMA_{14} *(V.P)*

Table 5. The Divergence of Price KE and SPE During Uptrends

Uptrend	Ideal Case	Weakness
Prices		
Price Simple Potential Energy		
Price Kinetic Energy		

Table 6. The Divergence of Price KE and SPE During Downtrends

Downtrend	Ideal Case	Strength
Prices		
Price Simple Potential Energy		
Price Kinetic Energy		

Like the IPWRI, the price kinetic energy index (KEI) and the simple potential energy index (SPEI) fluctuate around their zero-lines. They generate buying signals when the indexes cross the zero-lines upward and create selling signals when they cross the zero-lines downward. To construct the indexes, let

- $SPE_{today} = V.P$
- If $P_{today} > P_{yesterday}$; then $+SPE_{today}$
- If $P_{today} \leq P_{yesterday}$; then $- SPE_{today}$
- $SPEI = EMA_{14} (\pm SPE_{today})$
- $KE_{today} = 0.5\, V.(P-P_y)^2$
- If $P_{today} > P_{yesterday}$; then $+KE_{today}$
- If $P_{today} \leq P_{yesterday}$; then $- KE_{today}$
- $KEI = EMA_{14} (\pm KE_{today})$

SPE and KE represent market demand and supply, respectively. Figures 16, 17 and 18 clarify the relationships among the SPE, SPEI, KE, KEI (IPWRI) and prices. Since the SPEI and IPWRI are derived from SPE and KE, respectively, then any deviation by the indexes is a false representation. When prices rise, the price KE declines (normal behaviour). If the KE escalates along with prices, then this is considered a weakness. Also, it is ideal when the KE increases while prices are declining. If the KE drops when prices fall, then this is considered strength. Thus, the KEI or IPWRI usually shows positive divergences but false negative divergences. On another note, it is reasonable to see volatility continuation when prices decline because the KE rises (normal situation). Usually, when prices and KE rise, a volatile session (high range) will be preceded by relatively low volatile and sideway sessions, as shown in Figures 12 and 14.

Figure 16. FTSE 100 Index — Daily Chart

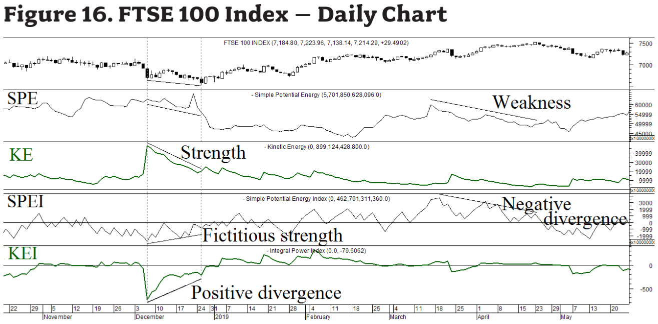


Figure 17. EGX: Commercial International Bank (COMI.CA) — Daily Line Chart

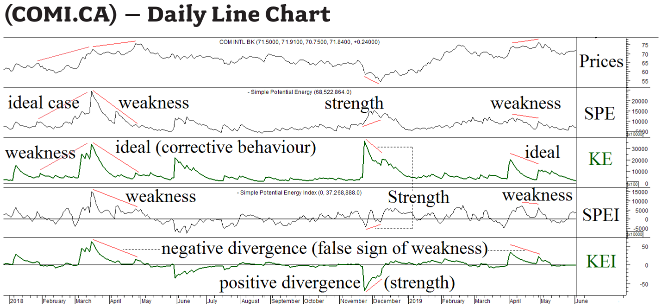
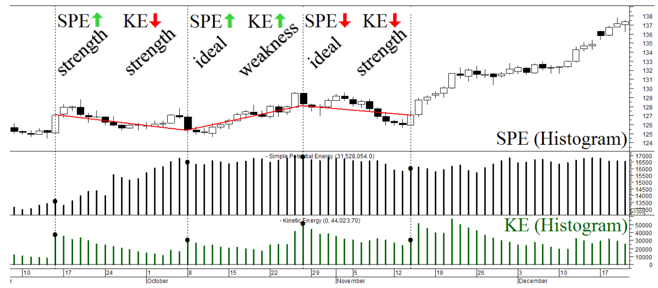


Figure 18. GBPJPY — Daily Chart



Conclusion

This article has highlighted the cyclical behaviour of the performance indicators and the use of their interaction to analyze the price motion. From this study, analysts can find that the edge of pressure over linear momentum indicators is by revealing excessive buying and selling pressure during a sideways squeeze. Unlike momentum indicators, they show negative divergences with prices that form higher highs with high ranges. Strength and dynamic strength indicators also have an edge at the end of corrections and counter-trend movements. They are the first among the performance indicators to follow the primary trend direction back. The IPWRI also detects weakness in prices earlier than the linear momentum index. The early detection was interpreted briefly by the interaction of new indicators SPE and SPEI with the integral power and prices. Such an interaction is the facet of a newly introduced concept in technical analysis—"Market Energy". This term also refers to market health.

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Serway, Raymond A., and John W. Jewett. *Physics for Scientists and Engineers*. 6th ed. Thomson Brooks/Cole, 2004.

Software and Data

Data and charts used in this article are provided by Thomson Reuters data feed and Metastock software.

The Measure Rule

By Thomas Bulkowski

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Summary: Use the measure rule to predict a price target after the breakout from a chart pattern.

In the second edition of my book, *Encyclopedia of Chart Patterns,* I explored how often a price prediction method called the measure rule works for over 60 chart and event patterns in both bull and bear markets. This article updates the results for various chart patterns, including how often the measure rule works and what to look for.

For most chart patterns, the measure rule is the height added to (upward breakouts) or subtracted from (downward breakouts) the breakout price. Figure 1 shows an example of the rule for an Eve & Eve double bottom.

Eve & Eve Double Bottom

An Eve & Eve double bottom has two valleys near the same price. Each valley appears wide and rounded. If spikes are present, they are usually short and clustered, like cut grass. Contrast the Eve bottom with an Adam bottom in October. An Adam bottom appears narrow, usually with a one- or two-day downward spike. The various combinations of Adam and Eve peaks or valleys for double tops and bottoms give performance and identification differences.

Figure 1. An Eve & Eve double bottom has a price target that matches the height of the chart pattern.

The time between the two bottoms of a double bottom varies, but the best performance comes from bottoms spaced three to seven weeks apart. Valleys wider than seven weeks show diminished performance after the breakout. The height of the pattern (as a percentage of the breakout price) from the lowest valley to the highest peak between the two valleys is at least 10 percent, but allow variations. Tall chart patterns often perform substantially better than short ones.

In the example shown in Figure 1, a throwback occurs after the breakout when the stock returns to the breakout price. A throwback happens 67 percent of the time in the 2,295 double bottoms I looked at.

To apply the measure rule to double bottoms, subtract the lowest valley in the chart pattern (B) from the highest peak (A) to get the height. Since the breakout is upward, add the height to the highest peak (A) to get a target price. Price reaches or exceeds the target 69 percent of the time in a bull market, or about two out of every three trades.

Head-and-Shoulders Bottom

A head-and-shoulders bottom, such as the one shown in Figure 2, has a left shoulder that is opposite a right shoulder with a head in between. The shoulder valleys should bottom near the same price and be almost an equal distance from the head. Symmetry is important for easy identification.

The head must be below the two shoulder valleys; otherwise, you may be looking at a triple bottom. A neckline joins the armpits in the pattern, and it signals a trade when price closes above it (for down-sloping necklines only). For up-sloping necklines, use a close above the price of the peak located between the head and right shoulder as the buy signal. Otherwise, you may never get a buy signal for steep necklines. Volume is usually heavier on the head or left shoulder and diminished on the right shoulder.

The measure rule is unique for head-and-shoulders patterns (both tops and bottoms). Find the lowest valley in the head and measure the vertical distance from that low to the neckline. I show the measure between the head and point A in Figure 2. That gives the height. Add the height to the breakout price—the point where price pierces the neckline (for down-sloping necklines) or the peak price between the head and right shoulder (for up-sloping necklines). The result is the target price. Price hits the target 73 percent of the time in a bull market.

Falling Wedge

A falling wedge is a somewhat rare pattern, and Figure 3 shows an example. A wedge is a price pattern bounded by two converging and down-sloping trendlines. The trendlines will eventually join at the wedge apex. The breakout averages 57 percent of the way to the wedge apex.

Look for price to come close to or touch each trendline a total of five times or more—three times on one side and two on the other. Anything less than five touches and the pattern may be invalid. Price should also cross the pattern from side to side several times like that shown. Volume usually trends downward from the start of the pattern to just before the breakout.

The measure rule for upward breakouts from falling wedges is the top of the pattern, point A in Figure 3. A downward breakout uses the height of the pattern (A–B) projected downward from the lowest valley in the pattern (B). Price reaches the top of the pattern 66 percent of the time in a bull market. For downward breakouts, the measure rule is less successful, working just 32 percent of the time. To increase the likelihood of a successful target, use half the height projected downward.

Symmetrical Triangle

Figure 4 shows a symmetrical triangle ABC. A symmetrical triangle is a chart pattern that has two converging trendlines that join at the triangle apex (C). The top trendline slopes downward, and the bottom one slopes upward. Look for at least two touches of each trendline, and make sure price crosses the chart pattern plenty of times, filling the pattern with price movement. Avoid cutting off a rounded turn and calling it a symmetrical triangle.

The traditional way to use the measure rule is to compute the height (A–B) and add it to the upward breakout price or subtract it from the downward breakout price. Price stages a breakout when it closes outside of the triangle trendline. This works 67 percent of the time for upward breakouts and 44 percent of the time for downward breakouts in a bull market.

An alternative way to compute a price target is to draw a line parallel to the bottom trendline (for upward breakouts like

Figure 2. A head-and-shoulders bottom uses the neckline as the vertical measure projected upward from the breakout point to compute a price target.

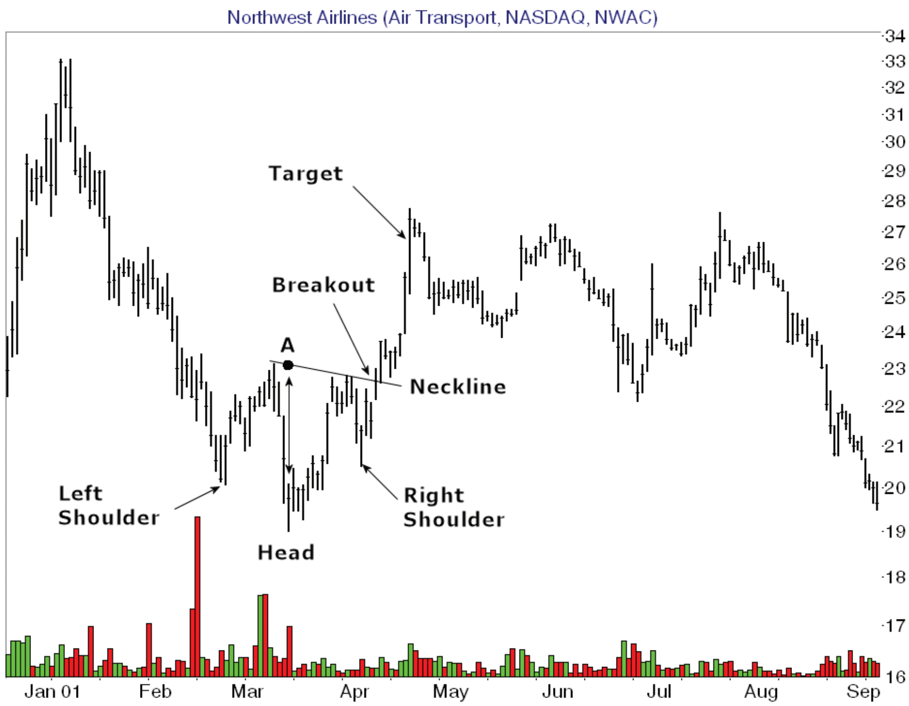
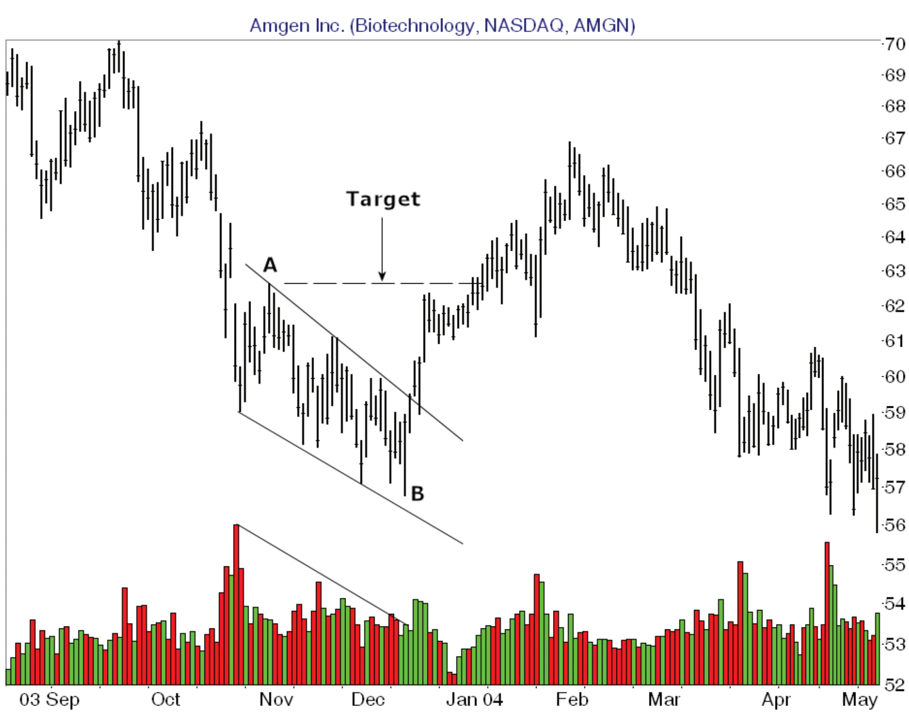


Figure 3. A falling wedge with an upward breakout needs price to rise to the top of the pattern to hit its target.



that shown by the dashed line) or parallel to the down-sloping line AC, beginning at point B, for downward breakouts. Begin drawing the line from the start of the pattern on the top (point A), ending directly above the breakout point (D). The price directly above the breakout becomes the target.

The Numbers

Table 1 shows how often the measure rule works for popular chart patterns. For example, I looked at a database of the various combinations of Adam & Eve double bottoms and found 837 chart patterns that I tested against the measure rule prediction. The rule worked between 66% of the time in a bull market using data from 1991 to 2018 in as many as 1,100 stocks, but not all stocks covered the entire period, and I excluded data from bear markets. That means price met or exceeded the target price before dropping at least 20% (a trend change, measured from the highest peak to the close) or a close below the lowest valley in the chart pattern.

Figure 4. A symmetrical triangle uses the pattern's height projected in the direction of the breakout to reach a target price, or a trendline parallel to the side opposite the breakout to get a target.

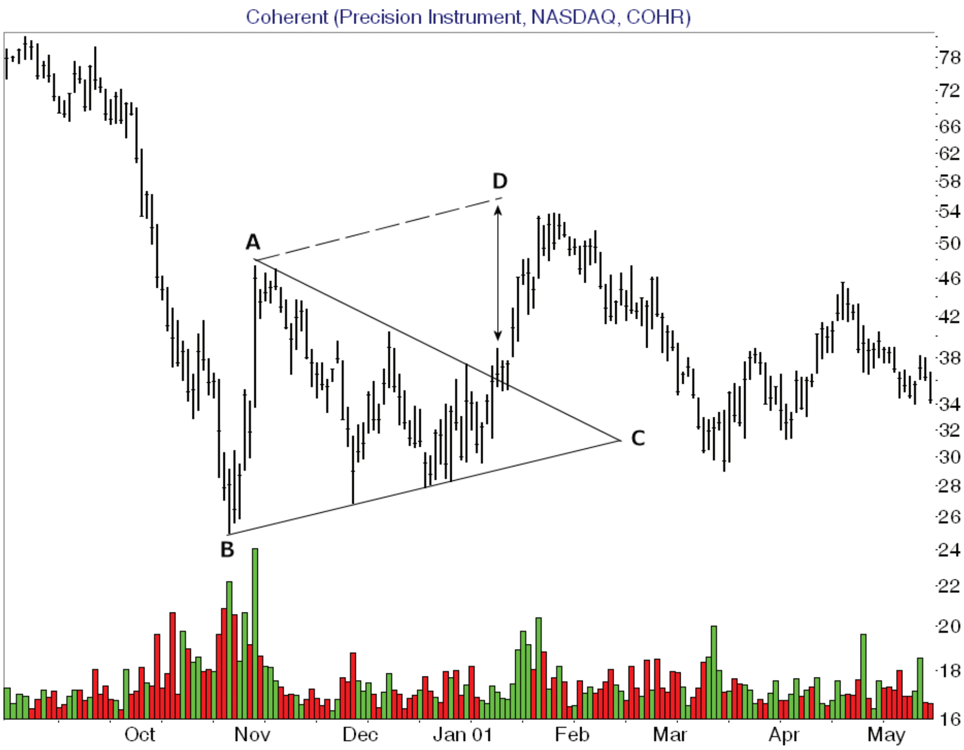


Table 1. The table shows how often the measure rule works for various chart patterns and breakout directions.

Chart Pattern	Upward Breakouts	Downward Breakouts
Double bottoms (all variations)	69%	N/A
Double tops (all variations)	N/A	45%
Head-and-shoulders bottoms	73%	N/A
Head-and-shoulders tops	N/A	58%
Triangles, ascending	70%	55%
Triangles, descending	73%	49%
Triangles, symmetrical	67%	44%
Triple bottoms	67%	N/A
Triple tops	N/A	48%
Wedge, falling	66%	32%
Wedge, rising	58%	46%

Notes: N/A means not applicable. All variations mean the four combinations of Adam & Eve shapes for peaks and valleys.

The table shows that price meets or exceeds the target better after an upward breakout than a downward one. For percentages below 50, use a projection that is half the height of the pattern. That will increase the probability that price will hit the target.

Closing Position

The measure rule is a tool used with chart patterns that suggests a price target. Typically, the height of the pattern is used in the computation. Add the height to upward breakouts or subtract it from downward ones to get a price target. For a more conservative (closer) target, use half the chart pattern height projected in the direction of the breakout.

Once you have a price target, look for nearby support or resistance zones. This may be round numbers (10, 15, 20, and so on), prior peaks and valleys, horizontal price consolidation regions, trendlines, and even other chart patterns. Often, price will stall at overhead resistance or underlying support as it nears the target price. Close out your position if price shows weakness or signs of reversing.

Optimal Leverage and Stopping Losses in Trading

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Abstract

Traders may use leverage to scale up the returns and use stop orders to limit their losses. Typically used for controlling risk, stop-loss orders may actually increase long-run trading profit. This paper derives a criterion for maximizing long-run trading profit with respect to leverage and stop-loss order placement, as both may affect profitability. In a trading application, we study how stopping losses and leverage affects trading profit. We find empirical support that stop-loss order placement *together* with leverage can have a substantial effect on long-run profit.

Introduction

Long-run profit in trading requires that the trader have an *edge* (i.e., able to generate a positive average return) when trading the financial markets. When using technical analysis, the trader decides when to enter and exit the market following a strategy based on historic information (e.g., moving averages, moving average convergence divergence, relative strength indicator) or a combination of strategies (Katz and McCormick, 2000, provide an overview of technical trading strategies). However, success in trading requires not only an edge, but the trader needs to also decide how many contracts to buy or sell in relation to the traders' capital (i.e., leverage), and to decide if and when one should get out of a losing trade (i.e., stopping losses) (Tharp, 1997; Faith, 2003; Tharp, 2007). This paper studies how to optimally use leverage and stopping losses to maximize the long-run profit of a given edge.

Traders may use leverage to scale up the returns and increase trading profit. Leverage in trading means that a trader controls a larger nominal amount than the current value of his trading capital (e.g., Lundström and Peltomäki, 2018; Lundström, 2018). Leverage strategies for trading are sometimes denoted *money management* (Sewell, 2011 provides an overview of leverage strategies). Interestingly for traders, large leverage factors do not necessarily transfer to large profits in the long run. In fact, Kelly (1956) shows that there exists a unique level of optimal leverage that maximizes the long-run profit of a given edge, but also that leverage above the optimal level actually *decreases* the long-run profit (see also Vince, 1990). The intuition is that a too large leverage factor leads to severe drawdowns in capital that take too long to recover from.

The perhaps most famous strategy to decide how much leverage to use to maximize trading profit is the Kelly criterion. Introduced in Kelly (1956), applicable to games with binomial outcomes, the Kelly criterion maximizes the expected profit per trade with respect to the leverage factor, and is today part of the mainstream finance literature (e.g., Bodie et al., 2014). Thorp (1969) extends the binomial-outcome-criterion of Kelly (1956) on stock market and derivatives trading, where the returns approximately follow a continuous probability density function. Henceforth, we refer to the criterion of Thorp (1969) as the Kelly criterion. Rotando and Thorp (1992) study the empirical trading results from buying S&P 500 contracts at the start of the year and selling the same contracts at the end of the year. They find sizable long-run profit when applying the Kelly criterion (Rotando and Thorp, 1992). Based on the Kelly criterion, Lundström and Peltomäki (2018) show empirically how an optimal level of leverage can increase the long-run profitability of Exchange Traded Products equipped with embedded leverage.

The Kelly criterion is not the only optimal leverage criterion applicable to trading. Independent of the Kelly criterion, Vince (1990, 2011) suggests an alternative criterion for maximizing long-run trading profit: the Optimal f. This criterion maximizes the expected profit per trade with respect to the position size (the maximum fraction of capital the trader expects to lose in each trade) relative to the largest expected loss of the trading returns, and hence not the leverage factor per se (e.g., Vince, 1990, 2011). This paper refers to it as the Vince criterion to avoid confusion. Anderson and Faff (2004) assess the profitability of the Turtle trading trend-following strategy made public in Faith (2003) in five futures markets reinvesting profits using the Vince criterion. They conclude that optimal leverage plays a more important role for the profitability in futures trading than previously realized, with large differences in profits depending on what leverage factor is applied (Anderson and Faff, 2004). Even if the Kelly and the Vince criteria typically are treated as essentially different leverage criteria in trading (see, for example, Vince, 2011), Lundström (2018) shows theoretically that the Kelly and Vince criteria produce identical profit when evaluated under the same assumptions.

Traders use stop orders to limit their losses (i.e., stop-loss orders). Stopping losses in trading is done by placing a buy (sell) order above (below) the market entry level for a short (long) position that will cover the position if the market moves a certain distance against the trader. We henceforth refer to this distance as the *stop distance*. The stop distance is typically set small enough to avoid large losses, if the trend reverses against the trader, but large enough to avoid whipsaws (i.e., a position is prematurely closed due to the volatility of the asset rather than a change in trend). Traders therefore typically set the stop distance based on some multiple of the volatility of the asset (e.g., Tharp, 1997; Williams, 1999; Faith, 2003; Anderson and Faff, 2004; Tharp, 2007). When based on historic information, we note that stopping losses can actually be viewed as a technical trading strategy in its own right. Stop-loss orders differ from trailing stop orders in that trailing stops are used to lock in profits while stopping losses limit losses.

In academic studies, stop-loss orders are somewhat considered in the context of optimal order selection algorithms (e.g., Easley and O'Hara, 1991; Biais et al., 1995; Chakravarty and Holden, 1995; Handa and Schwartz, 1996; Harris and Hasbrouck, 1996; Seppi, 1997; Lo et al., 2002). In these studies, we note that the use of stopping of losses is generally explained as a mechanism for avoiding or anticipating pitfalls of human judgment. Shefrin and Statman (1985) and Tschoegl (1988) consider behavioral patterns that may explain the popularity of stop-loss orders as a risk-control technique.

Kaminski and Lo (2013) provide the first academic study on how stop-loss orders effect the returns and profit from trading. They show that stop-loss orders can actually increase the long-run profit of trading when the markets trend (i.e., when the returns follow [time series] momentum). The rationale is that if returns follow momentum, small losses tend to grow into larger losses, and by stopping losses before they grow large, the stop-loss should increase the expected return of trading in the long run. Kaminski and Lo (2013) find empirical support of an increase in the average return when stop-loss orders are added to a buy and hold strategy applied to monthly returns data for U.S. equity indices from January 1950 to December 2004.

Leverage and stop-loss orders are typically determined independent and separately from each other, the first motivated for increased profit and the second one motivated from a risk-management perspective. For example, stop-loss orders are not explicitly modeled in the Kelly or Vince criteria. Since both leverage and stop-loss order placement may affect profitability when markets trend, we posit in this paper that leverage and stop-loss placement should be determined jointly.

This paper derives a criterion for maximizing long-run trading profit with respect to leverage and stop-loss order placement, as both may affect profitability. In a futures trading application, we study how various stop-loss order placements and optimal leverage affects trading profit when markets trend. We find empirical support that stop-loss order placement *together* with optimal leverage can have a substantial effect on profit. Further, we find the perhaps counterintuitive result that stops placed very close to the entry price increase long-run profit dramatically, even if it results in a large number of whipsaws. The findings of this paper suggest that traders may have a lot to gain from determining leverage and stop order placement jointly when markets trend, and that profit-maximizing traders should not necessarily be afraid of whipsaws.

We continue this paper by presenting the Kelly and Vince criteria and introducing stop-loss orders. The section after that describes the data and gives the empirical results. The last section concludes.

Leverage Strategies in Trading

Traders may use leverage to scale up the returns and increase trading profit. This paper models the returns and profit from trading as follows. Suppose that x denotes the return of a trade for a given trading strategy and is expressed as a percent. Following the standard assumptions in the optimal-leverage literature, assume that the trading returns are generated from a continuous probability density function $h(x)$ known to the trader (e.g., Thorp, 1969; Rotando and Thorp, 1992; Lundström, 2018). Given these assumptions, the edge from trading can be written: $E(x) = \int_a^b x\, h(x)dx = \mu > 0$, where a is the largest loss and b is the largest win generated by the strategy. When the returns of each trade are reinvested, the wealth from trading is given by the function, $V_n = V_0 \prod_{i=1}^{n}(1 + x_i)$, where $V_0 > 0$ is the initial level of wealth, and V_n is the level of wealth after n trades.

The effect of leverage on trading profit can then be illustrated as follows: When applying a fixed leverage factor, $\theta > 0$, on each trade i, the profit from trading can be illustrated as the trader's Terminal Wealth Relative (TWR) to the initial level of wealth (e.g., Vince 1990, Lundström, 2018);

$$TWR_n = \frac{V_n}{V_0} = \prod_{i=1}^{n}(1 + \theta x_i) \tag{1}$$

where a leverage factor of, $0 < \theta < 1$, $\theta = 1$, or $\theta > 1$, corresponds to a smaller, equal, or larger exposure, respectively, relative to the committed capital. We note that a constant leverage factor follows from a constant edge.

We can then write the profit per trade as:

$$G_n = \frac{1}{n}\ln\left(\frac{V_n}{V_0}\right) = \frac{1}{n}\sum_{i=1}^{n}\ln(1 + \theta x_i) \tag{2}$$

Throughout this paper, we refer to TWR and G_n interchangeably as profit. This simplifies the terminology and should cause no conceptual confusion since the latter is a monotonic transformation of the former. We now turn to the Kelly and Vince criteria to answer how much leverage a profit-maximizing trader should use.

The Kelly Criterion

The Kelly criterion maximizes the expected profit per trade with respect to the leverage factor (Kelly, 1956). When the returns are continuously distributed, Thorp (1969), Rotando and Thorp (1992), and Lundström (2018) propose an expected profit per trade of:

$$G(\theta) = E\{G_n(\theta)\} = E\left\{\frac{1}{n}\sum_{i=1}^{n}\ln(1 + \theta x_i)\right\} = \int_a^b \ln(1 + \theta x)\, h(x)dx \tag{3}$$

with a maximum at $\theta = \theta^*$ when $G'(\theta^*) = \int_a^b x\,(1 + \theta^* x)^{-1} h(x)dx = 0$. See Thorp, 1969, or Rotando and Thorp, 1992, for proofs. We note that $\theta^* > 0$ as long as $\mu > 0$, avoiding the uninteresting corner solution $\theta^* = 0$. We further note that $G(\theta)$ is increasing in μ (i.e., $\frac{dG(\theta)}{d\mu} > 0$, *ceteris paribus*) (see the discussion in Lundström and Peltomäki, 2018).

Using the Kelly criterion has many valuable properties for a trader. In the long run, Breiman (1961) showed that the Kelly criterion maximizes long-term growth and asymptomatically outperforms any other essentially different leverage strategy. Breiman (1961) also showed that the Kelly criterion minimizes the expected time it takes to reach a certain level of capital, which can be valuable to traders that experienced a severe drawdown and would like to use leverage to minimize the time to get back to the previous high.

The implication of optimal leverage in trading is striking: that too small a leverage factor ($\theta < \theta^*$) leads to a lower long-term profit than is feasible, but also that too large a leverage factor ($\theta > \theta^*$) leads to a lower long-term profit than is feasible. The intuition is that a too large leverage factor leads to severe drawdowns in capital that take too long time to recover from.

The Vince Criterion

The Vince criterion maximizes the expected profit per trade with respect to the position size (i.e., the maximum fraction of capital the trader expects to lose in each trade) relative to the largest expected loss of the trading returns (e.g., Vince, 1990, 2011). To compare the profit of the Vince criterion to the Kelly criterion, we here illustrate the Vince criterion with the assumptions of this paper.

If we refer to f_V as the position size, the expected profit per trade can be written as (see also Lundström, 2018):

$$G(f_V) = E\{G_n(f_V)\} = \int_a^b \ln\left(1 + \frac{f_V}{|a|}x\right)h(x)dx \tag{4}$$

with a maximum at $f_V = f_V^*$ when $G'(f_V^*)=0$, yielding an optimal leverage factor of: $\theta^*_V = \frac{f_V}{|a|}$ (see Vince, 1990, 2011). Note that f^*_V is always a fraction of capital as $(0 < \theta^* < -1/\alpha) = (0 < f^*_V / |\alpha| < -1/\alpha)$ and, by multiplying $|\alpha|$ throughout with , we obtain $0 < f^*_V < 1$.

Since the Kelly and Vince criteria produce identical profit when evaluated under the same assumptions, it follows that: $\theta^* = f^*_V / |\alpha|$ (for proof, see Lundström, 2018). However, since the position size adds information about the maximum expected loss per trade, we introduce stop-loss orders to the Vince criterion unless otherwise stated.

Introducing Stopping of Losses

Traders use stop-loss orders to limit their losses. Stopping losses in trading is done by placing a buy (sell) order above (below) the market entry level for a short (long) position that will cover the position if the market moves a certain distance against the trader. We define the stop distance, $s < 0$, as a negative return from the opening price of the position, expressed in percent, on the interval $s \in [\alpha, \delta]$. We consider the largest stop distance (least negative), δ, to be strictly negative for practical reasons (if $\delta = 0$ we would stop all trades due to positive bid-ask spreads in applications), and we limit the smallest stop distance to (if $s \leq \alpha$, s is no longer a binding restriction on x).

When applying stop-loss orders placed a stop distance from the entry price, the trading returns equal s for stopped out trades, or x for surviving trades. The trader thereby restricts the maximum loss on every trade and censors the left tail of $h(x)$ at s. In this paper, we assume that n is large, and we do not re-enter a stopped out position during the remainder of the trading period (both the Kelly and Vince criteria are long-run results based on a large number of trades).

Stopping losses mechanically at a certain distance from the entry price, as we do in this paper, resembles the classic filter rule of Alexander (1961). A filter rule buys X % from a previous low and sells X % from a previous high. Stopping losses at below entry price can be interpreted as an intraday filter rule sell signal from the opening price. For stop-loss orders to affect the expected return from trading, markets must trend (i.e., trading returns must follow [time series] momentum) (Kaminski and Lo, 2013). The argument is as follows: If markets trend, stopping a loss prematurely at level will arguably lead to a smaller loss on average than if the trade is left unrestricted and covered by the trading strategy. A smaller loss on average, but without affecting the winning trades on average, will translate into a larger expected return from trading. However, if asset prices are Brownian motions with zero drift, stopping losses will not affect the expected return from trading (e.g., Kaminski and Lo, 2013).

Since both leverage and stop-loss order placement may affect profitability when markets trend, we posit that leverage and stop-loss placement should be determined jointly and propose a new criterion also taking stopping of losses into account.

A Criterion for Optimal Stopping of Losses

When applying stop-loss orders in trading, the leverage factor should ideally be constructed so that the losses from leveraged trading should be limited to the position size (e.g., Tharp, 1997; Faith, 2003; Tharp, 2007). In line with this reasoning, and inspired by the Vince criterion, this paper proposes a leverage factor on the interval $s \in [\alpha, \delta]$ of

$$\theta_c(f_c, s) = \frac{f_c}{|s|} > 0 \tag{5}$$

where c indicates censoring by a stop-loss and f_c is the position size when stopping of losses is applied.

When applying the leverage factor in Eq. (5), the leveraged trading returns are $\theta_c s = f_c/|s|\, s = -f_c$ for stopped out trades and $\theta_c x = f_c/|s|\, x$ for surviving trades. Hence, the largest loss of capital per trade is limited to the position size by construction. We may then write the TWR after a total of n trades, with S stopped out trades and $n - S$ surviving trades, as:

$$TWR_n = \frac{V_n}{V_0} = (1 + \theta_c s)^S \prod_{i=1}^{n-S}(1 + \theta_c x_i) = (1 - f_c)^S \prod_{i=1}^{n-S}\left(1 + \frac{f_c}{|s|}x_i\right) \tag{6}$$

We can then write the expected profit of trade as:

$$G(f_c, s) = E\left\{\frac{1}{n}\left(S\ln(1 - f_c) + \sum_{i=1}^{n-S}\ln\left(1 + \frac{f_c}{|s|}x_i\right)\right)\right\}$$

$$= E\left\{\frac{S}{n}\ln(1 - f_c) + \frac{n-S}{n}\frac{1}{n-S}\sum_{i=1}^{n-S}\ln\left(1 + \frac{f_c}{|s|}x_i\right)\right\} \tag{7}$$

$$= p(s)\ln(1 - f_c) + [1 - p(s)]\int_s^b \ln\left(1 + \frac{f_c}{|s|}x\right)h(x)dx$$

where $p(s)$ is the probability of stopped out trades and $1 - p(s)$ is the probability of surviving trades.

We obtain the profit maximum by maximizing the expected profit per trade (7) with respect to f_c and s, subject to the constraint $a \leq s \leq \delta$. If $G(f_c, s)$ is differentiable as s, we obtain the maximum: $G(\theta^*_c)$ at $\theta = \theta^*_c = (f^*_c|s^*|)$, when $Gf(f^*_c) = 0$ and $G_s(s^*) = 0$, or at corner solutions $G(f^*_c, \alpha)$, $G(f^*_c, \delta)$, given that $\mu(s) > 0$ on the interval $[\alpha, \delta]$. Here, $Gf = \frac{\delta G}{\delta f}$ and $Gs = \frac{\delta G}{\delta s}$. If $G(f_c, s)$ is *not* differentiable as s, we may instead solve the profit maximum by using numerical methods (for numerical methods suitable for maximizing the profit with respect to the position size, see

Vince, 1990). Conditional on s, we expect that the results of Breiman (1961) still hold for the stopping of losses criterion.

The novelty of the stopping of losses criterion (7) compared to the Kelly and Vince criteria stems from the profit being maximized with respect to both the position size and the stop distance (here an endogenous variable), and not only with respect to the leverage factor or the position size. We note that f_c^* is always a fraction of capital as as $(0 < \theta_c^* < -1/s) = (0 < f_c^*, / |s| < -1/s)$ and, by multiplying throughout with $|s|$, we obtain $0 < f_c^* < 1$. As the profit accounts for both the continuously distributed returns of the surviving trades and for the returns of the stopped out trades, it can be seen as a mixture of the Kelly criterion of Kelly (1956) and of the Kelly criterion of Thorp (1969). Further, the expected profit per trade (7) equals the Vince criterion expected profit per trade when $s = \alpha$:

$$p(s)\ln(1-f_c) + [1-p(s)]\int_s^b \ln\left(1+\frac{f_c}{|s|}x\right)h(x)dx = \int_a^b \ln\left(1+\frac{f_V}{|a|}x\right)h(x)dx$$

since $p(s) = 0$ when $s = \alpha$.

To study how much more profit a trader stands to gain by using the stopping of losses criterion relative to the Kelly or Vince criteria, we compare profit levels for different values of s, given their optimal position sizes.

If we denote $G(f_c^*|s,s)$ the maximum profit conditional on s (f_c^* is the optimal leverage factor conditional on s), we are able to study the difference in maximum profit between using s^* and an arbitrary stop distance, s, by comparing maximum profit levels $G(f_c^*, s^*)$ with $G(f_c^*|s,s)$. The profit level $G(f_c^*|s,s)$ here illustrates the maximum profit levels in terms of optimal leverage for all other levels of s than s^*. For example, the quotient $\Pi(s) = \frac{G(f_c^*, s^*)}{G(f_c^*(s), s)} \geq 1$ then measures the relative profit from using the optimal stop distance instead of an arbitrary stop distance, where $\Pi(s)>1$ indicates a positive profit by applying optimal stopping of losses, and where $\Pi(s)=1$ indicates no relative profit. That is, the measure $\Pi(s)$ "isolates" the stopping of losses effect on maximum profit from the optimal leverage effect.

However, to get an idea of how much more profit a trader stands to gain by using the stopping of losses criterion relative to the Kelly or Vince criteria when markets trend, we must turn to empirical estimation. This brings us to the trading application.

Trading Application

We estimate the empirical profit when adding optimal leverage and stop-loss orders to a buy and hold strategy. We note that the buy and hold strategy is used as a benchmark strategy when estimating the empirical trading profit when trading with optimal leverage, as in Rotando and Thorp (1992), but also when trading with stop-loss orders, as in Kaminski and Lo (2013), making it a suitable candidate.

The effect on trading profit from applying optimal leverage, as documented in Kelly (1956), Breiman (1961), and others, are asymptotic results (when $n \to \infty$), and we therefore need a large number of trade observations for accurate profit estimations. By adding stop-loss orders, we need an even larger number of trade observations. This is because stop-loss orders censor the trades reaching sometime during the lifetime of the position, thereby reducing the number of trade observations used to estimate $h(x)$. Rotando and Thorp (1992) estimate profit based on annual returns and Kaminski and Lo (2013) on monthly returns. For example, with an annual holding period from 1926 to 1984, the empirical results of Rotando and Thorp (1992) are based on a total of 59 trades. This paper therefore suggests a buy and hold strategy based on *daily* returns on long time series, buying on the open and selling on the close.

Data

Stopping losses may increase the expected return of trading, but only when the markets trend. The challenge of this paper is to find long times series of actually traded futures contracts of markets that trends intraday (i.e., display intraday momentum). Further, to accurately estimate the effect of stopping losses on profit, not only do we need daily price observations of open and close, but also intraday price readings to verify if the stop distance was exceeded sometime during the trading day.

To meet this challenge, we use the same data of S&P 500 stock market index futures contracts and crude oil futures contracts as in Lundström (2019) for assessing the (unleveraged) profitability of the Opening Range Breakout (ORB) strategy. The ORB strategy profit is based on intraday momentum, and since Lundström (2019) find empirical support of positive average ORB returns after costs, we infer that both markets contain momentum.

The S&P 500 price series covers the period April 21, 1982, to November 29, 2010, and the crude oil price series covers the period January 2, 1986, to January 26, 2011. The series is obtained from Commodity Systems Inc. (CSI) and is delivered in the format: open, high, low, and close of daily price readings of actually traded futures contracts. We analyze these series separately and independently of each other.

We assess the return of trading day i by: $x_i = close_i/open_i - 1$, μ by $\bar{x} = n^{-1}\sum x_i$, and use $a = min(x_i)$.

Table 1 shows some descriptive statistics.

Table 1. Descriptive Statistics of the Return Series

	Obs.		Std.Dev	Min	Max	Skewness	Kurtosis
S&P 500	7218	0.0001	0.0081	-0.0912	0.0808	-0.1508	17.35
crude oil	6264	0.0001	0.0093	-0.0736	0.0742	-0.1160	8.45

Table 1 shows that the average returns, $\bar{x}$, are small, albeit positive. We note that small means close to zero, and positive kurtosis are typical results for empirical returns series (e.g., Cont, 2001). The number of observations (Obs.) is considerably higher than the 59 observations used in the study of Rotando and Thorp (1992). This paper interprets (Min) as the most negative trading return for each asset. As in Vince (1990, 2011), represents the minimum *holding period* return, not the minimum *intraday* return.

Stopping losses censors trades equal to the level of stop distance, , sometime during the trading day. Inspired by the approach used in Lundström (2019), we assess the returns of an intraday trading strategy using the information of the open, high, low, and close of daily price data. This paper assesses the returns when trading with a stop-loss by: $x_i\,(l_i > s) = x_i$ and $x_i\,(l_i \leq s) = s$, where $l_i = \frac{low_i}{open_i} - 1$ and , where represents the lowest intraday return during trading day i. That is, if the lowest intraday return reaches the stop distance, we know that the stop-loss order is executed sometime during the trading day.

Estimating Profit

From Lundström (2018) we know that the Kelly and Vince criteria by Eq. (2) and (3) yield identical profitability, and we therefore only report the empirical results of the Vince criterion if not otherwise stated. When applied to long time series of daily data, this paper estimates the expected profit per trade of the Vince criterion Eq. (4) by its sample mean:

$$G_n(f_V) = \frac{1}{n}\sum_{i=1}^{n} \ln\left(1 + \frac{f_V}{|a|}x_i\right),$$

and the stopping of losses criterion Eq. (7) by its sample mean:

$$G_n(f_c, s) = \frac{S}{n}\sum_{i=1}^{n} \ln\left(1 + \frac{f_c}{|s|}s\right) + \frac{n-S}{n}\sum_{i=1}^{n-S} \ln\left(1 + \frac{f_c}{|s|}x_i\right),$$

where we use $\frac{S}{n} \approx p(s)$.

For the stopping of losses criterion, we estimate maximum profit conditional on s; $G(f_c^*|s)$, by calculating a number of values of its sample mean $G_n(f_c|s)$ for different values of f_c over the discrete valued $f_c \in (0, 0.0025, 0.0050, \ldots, 0.9975)$ domain of for a given s. We then $q:th$ fit a degree polynomial, $G(f_c|s)$, based on these calculated values, to estimate the functional form of $G(f_c|s)$ with respect to f_c given s. We use tilde ~ and drop the subscript n for notational convenience, when we refer to the estimated polynomial. With the data at hand, we apply the step size of 0.25 percentage units in f_c, as we find it small enough to generate a graphically "smooth" functional form $\tilde{G}$ with respect to f_c without apparent corners. As the polynomial fit is local, we consider only positive values of $G_n(f_c|s) > 0$. As the polynomial $\tilde{G}$ is differentiable in f_c, we then analytically solve for the f_c^* that maximizes $\tilde{G}(f_c|s)$. By inserting f_c into the original function, $G_n(f_c^*|s)$, we finally obtain the maximum profit level conditional on . We use Ordinary Least Squares (OLS) estimators for the polynomial regressions.

For the Vince criterion, we calculate a number of values of $G_n(f_V)$ over the same discrete valued domain as we used before: $f_V \in (0, 0.0025, 0.0050, \ldots, 0.9975)$. To estimate the functional form of $G(f_V)$ with respect to f_V, we fit $q:th$ a degree polynomial, $\tilde{G}(f_V)$, based on the calculated values of $G_n(f_V)$. We then analytically solve for the f_V^* that maximizes $\tilde{G}(f_V)$ and by inserting f_V^* into the original function, $G(f_V)$, we obtain the profit maximum: $G_n(f_V^*)$.

However, $G_n(f_c^*|s)$ gives only one value of maximum profit for a given level of s. By collecting the maximum profit levels for each level of s over the discrete valued domain: $s \in \{\alpha, \ldots, \delta\}$ we can discern how maximum profit behaves in the dimension: $G_n(f_c^*|s,s)$. To simplify, we write: $\pi(s) = G_n(f_c^*|s,s)$. To study how maximum profit behaves in the s dimension, we estimate the functional form of $\pi(s)$ by fitting a $q:th$ degree polynomial, $\tilde{\pi}(s)$, based on the calculated values of maximum profit levels $G_n(f_c^*|s,s)$ obtained for each s. We expect to find the (global) maximum profit $G(f_c^*, s^*)$ when the function $\pi(s^*)$ attains its maximum on the interval $s \in [\alpha, \delta]$.

From the (Min) of x from Table 1, we set the most negative trading return to a=−0.0912 and a=−0.0736 for S&P 500 and crude oil, respectively. We set $\delta = -0.005$ to limit the largest (least negative) stop distance for both the S&P 500 and crude oil time series. We argue that $\delta = -0.005$ are reasonable levels as they are narrow enough to stop out more than one third of all trades but still wide enough to account for temporary large bid-ask spreads during volatile market periods, for both assets. We apply a step size of 0.5 percentage units in s as we find it small enough to generate a graphically "smooth" functional form of $\tilde{\pi}(s)$ with respect to without apparent corners.

Empirical Results

We estimate $\pi(s)$ with a third-degree polynomial for both assets (q=3). For the S&P 500, we obtain: $\tilde{\pi}(s) = 0.0008 + 0.1027s + 5.3368s^2 + 96.58s^3$, with R^2=1.00. For crude oil, we obtain: $s = 0.0009 + 0.1208s + 5.8416s^2 + 98.56s^3$, with R^2= 1.00. Calculations show that both polynomials $\tilde{\pi}(s)$ are strictly increasing in s; $\tilde{\pi}'(s) > 0$, with (corner solution) profit maxima; $\tilde{\pi}(-0.005)$, at $s = s^* = -0.005$ for both assets, respectively.

Calculations show that we obtain maximum profit at for both assets. When trading S&P 500, we obtain the profit maximum at $\theta^* = \frac{0.026}{0.005} = 5.22$, yielding the TWR = 18.40, which is $\prod = 8.33$ times the profit of the Vince criterion without stops. When trading crude oil, we obtain the profit maximum at $\theta^* = \frac{0.026}{0.005} = 5.00$, yielding the TWR = 17.77, which is $\prod = 11.85$ times the profit of the Vince criterion without stops. This shows that considerable relative profits can be made if the trader combines optimal stop distances with optimal leverage, relative to optimal leverage without stops, for both assets.

Table 2 summarizes the empirical results for four levels of s, including the unconstrained maximum for $s = s^* = \delta$. The results of the Vince criterion are presented in the first row for each asset, respectively. As a reference to the results of Kaminski and Lo (2013), we also present the trading profit without leverage (using $\theta = 1$). Figures 1 and 2 present the accumulation of wealth (in log scale) over time for traders using the stopping of losses criterion and the Vince criterion, applied to S&P 500 futures and to crude oil futures, respectively. As a reference, we also present the wealth accumulation over time for a trader who instead bought and held the underlying asset without leverage.

In Table 2, the $|s|$ is the absolute value of the stop distance, and $p(s)$ gives the frequency of stopped out trades. The $\pi(s)$ gives the average returns, and $s.e.$ the associated standard errors. The polynomial fit is optimized using OLS, where f^* gives the optimal fraction of the polynomial, the q gives the degree of the polynomial, the R^2 is the goodness of fit measure, and $\theta^* = \frac{f^*}{(s)}$ is the optimal leverage factor. The TWR and TWR^* give the profit when $\theta = 1$ and $\theta = \theta^*$, respectively. The $\prod(s)$ gives the relative profit if traders instead use the optimal stop distance. We use the notation of (-) to illustrate the results when applying the Vince criterion.

Table 2 shows that the average returns, $\mu(s)$, are small, albeit positive. When trading without leverage (using θ=1), we find only moderate positive effects on profit, yielding at most

Table 2. Empirical results

	$\theta = 1$					$\theta = \theta^*$					
	$\lvert s \rvert$	$p(s)$	$\pi(s)$	$s.e.$	TWR	f^a	q	R^2	θ^*	TWR^*	$\prod(s)$
S&P 500	-	0.00	0.0001	0.0001	1.88	0.160	2	0.99	1.75	2.21	8.33
	0.020	0.03	0.0001	0.0001	1.78	0.039	2	0.99	1.93	2.12	8.68
	0.015	0.06	0.0001	0.0001	1.91	0.034	2	0.99	2.27	2.56	7.19
	0.010	0.13	0.0001	0.0001	2.27	0.028	4	1.00	2.80	4.42	4.16
	0.005	0.31	0.0002	0.0001	2.72	0.026	4	1.00	5.22	18.40	1.00

	$\lvert s \rvert$	$p(s)$	$\pi(s)$	$s.e.$	TWR	f^a	q	R^2	θ^*	TWR^*	$\prod(s)$
crude oil	-	0.00	0.0001	0.0001	1.48	0.089	2	1.00	1.21	1.50	11.85
	0.020	0.05	0.0001	0.0001	1.45	0.026	2	1.00	1.32	1.48	12.01
	0.015	0.08	0.0001	0.0001	1.68	0.026	2	0.99	1.73	1.87	9.50
	0.010	0.16	0.0002	0.0001	2.20	0.024	4	1.00	2.42	3.67	4.84
	0.005	0.37	0.0002	0.0001	2.83	0.025	4	1.00	5.00	17.77	1.00

roughly 100 percent, and increase in *TWR* when applying stop-loss orders, for both assets. Table 2 also shows that profits are substantially increased when we combine optimal leverage factors with the stop distances, especially for the "aggressive stops," with small stop distances only fractions of the return standard deviations. Thus, stops placed very close to the entry price increase long-run profit dramatically when markets trend, even if it results in a large number of whipsaws. These findings suggest that traders may have a lot to gain from determining leverage and stop order placement jointly when markets trend, and that profit maximizing traders should not necessarily be afraid of whipsaws.

Regarding the results of the Vince criteria, the careful reader may note that $G_n(\theta^*_v) \geq G_n(\theta^*_c)$ at $s = \alpha$ in Table 2. These are not calculation errors, but because α is based on $min(x_i)$, not $min(l_i)$, where $min(x_i) \geq min(l_i)$, so that stopped out trades at α always recover to $x \geq \alpha$ in the end. This effect still lingers for stop levels relatively close to α, which explains the minor drop in *TWR* at $s = -0.02$ for both assets.

Figure 1. Wealth over time expressed in log levels when trading S&P 500 futures using the stopping of losses criterion (SoL) and the Vince criterion (Vince), both starting with $1 million USD, from April 21, 1982, to November 29, 2010. B&H refers to the profit from the buy and hold strategy. Trading costs are not included.

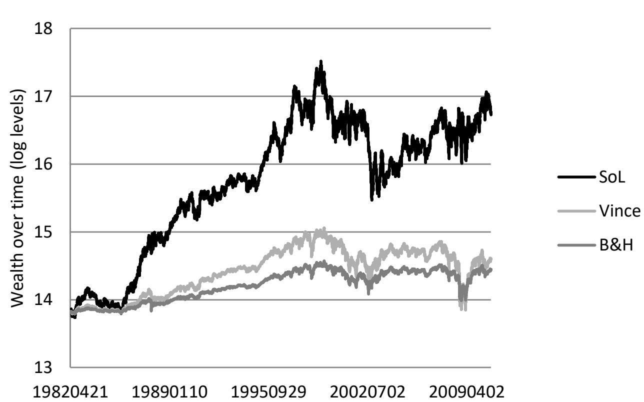
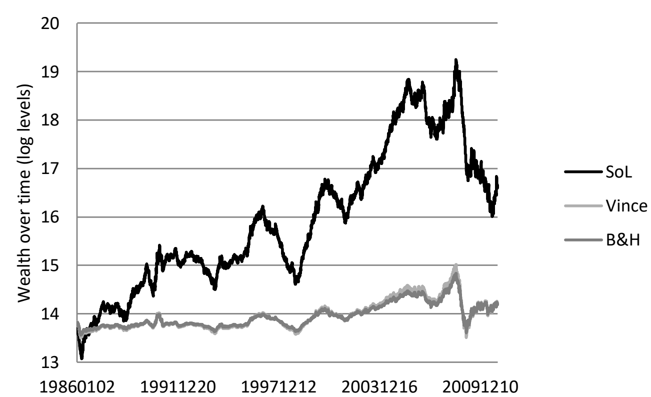


Figure 2. Wealth over time expressed in log levels when trading crude oil futures using the stopping of losses criterion (SoL) and the Vince criterion (Vince), both starting with $1 million USD, from January 2, 1986, to January 26, 2011. B&H refers to the profit from the buy and hold strategy. Trading costs are not included.



Figures 1 and 2 graphically illustrate that wealth accumulates quickly over time when combining optimal leverage factors with stop-loss orders but with very high volatility. We see that wealth levels from applying the stopping of losses (SoL) criteria substantially outperform the wealth levels from applying the Vince criteria (Vince) as well as the buy and hold (B&H) strategies, for both assets. Further, it appears that the outperformances of the SoL criteria are reasonably constant over time, suggesting that outliers of a few but extreme observations do not drive the results.

To verify positive outperformances, we also test the significance of the holding-period-returns for each calendar year. We calculate the criteria return of year k by: $ret_k = TWR_k - 1$, starting at the beginning of the calendar year and ending at year end. Each year consists of roughly $k = 240$ trades. We then estimate the average outperformance over time by the regression:

$$ret_k = \overline{ret} * 1 + v_k \tag{8}$$

where $\overline{ret}$ estimates the average outperformance and $v_{p,t}$ is the random error term.

To assess the statistical significance of regression (8), we apply Ordinary Least Squares (OLS) estimation using Newey-West Heteroscedasticity and Autocorrelated Consistent (HAC) standard errors, as trading strategy returns could possibly experience serial correlation. Table 3 shows the results.

Table 3. Profitability test when trading with $\theta = \theta^*$

		SoL	Vince	B&H	SoL-Vince	SoL-B&H	Vince-B&H
	$\overline{ret}$	0.16***	0.04	0.03	0.12***	0.13***	0.01
S&P 500	s.e.	0.06	0.03	0.02	0.06	0.06	0.01
	Obs.	28					
		SoL	Vince	B&H	SoL-Vince	SoL-B&H	Vince-B&H
	$\overline{ret}$	0.30***	0.04	0.03	0.26***	0.27***	0.01
crude oil	s.e.	0.14	0.04	0.04	0.12	0.12	0.01
	Obs.	24					

In Table 3, the $\overline{ret}$ is the average $TWR - 1$ for each year and *s.e.* the Newey-West HAC standard errors. SoL is the stopping of losses criterion, Vince is the Vince criterion, and B&H is the buy and hold strategy. SoL-Vince, SoL-B&H, Vince-B&H are the differences in the average annual TWR between the criteria. The asterisks *, **, and ***, refer to statistical significance at the 10%, 5% and 1% levels.

Table 3 shows that the stopping of losses criteria produces annual returns significantly larger than zero in both absolute terms (SoL) and in relative terms against the Vince criteria (SoL-Vince) and the buy and hold strategies (SoL-B&H), for both assets. Table 3 also shows that the buy and hold strategies (B&H) and the Vince criteria (Vince) do not generate significantly larger returns than zero for either asset. Further, even if profits increase somewhat when using the Vince criteria (see Table 2), Table 3 illustrates that the Vince criteria do not produce annual returns significantly larger than the returns of the buy and hold strategies (Vince-B&H) for either asset.

Sensitivity Analysis Regarding Trading Cost and Price Jumps

Up to this point, we have assumed zero trading costs and no slippage. Calculations show that taking trading costs into account would unfortunately decrease the average returns of our buy and hold strategy to below zero, leading to trivial results when applying leverage. Focusing here on the *relative* profit between criteria, stopping losses without re-entry does not generate more trades than the Vince criterion. Thus, we expect that adding costs does not alter the *relative* profit differences reported in this paper in any significant way.

Admittedly, lack of liquidity and possible price jumps resulting in slippage will consume some of the trading profits of the SoL criterion relative to the Vince criterion, as stop orders are not necessarily executed at the predetermined level *s*. Given the high level of liquidity during U.S. market trading hours for the assets studied in this paper, we expect price jumps to be relatively small. We consider here a reasonable estimate of 2 basis points when trading S&P 500 and crude oil futures (Empirical observations when trading futures contracts using an account size of around $1 million USD (Interactive Brokers, www.interactivebrokers.com, February 2, 2010 to November 29, 2010). Given an optimal stop level of $s = -0.005$, price jumps would then, on average, delay the position exit to $s = -0.0052$ for stopped out trades. Aware of the average level of price jumps, the trader then adjusts the optimal fraction correspondingly, and from the polynomials, $\tilde{\pi}(s)$, we obtain a reduced profitability of $TWR^* = 17.51$ when trading the S&P 500 and $TWR^* = 13.53$ when trading crude oil, when $s = -0.0052$. Although reduced, there still remain considerable levels of profitability relative to the existing criteria for both assets.

Concluding Discussion

This paper derives a criterion for maximizing long-run trading profit with respect to both leverage and stop-loss order placement based on the Kelly and Vince criteria. In a trading application, we study how various stop-loss order placements affect the long-run trading profit, given optimal leverage levels when markets trend.

When combining stopping losses with optimal leverage, we find a maximum difference of profits of 8 and 12 times relative to the Vince criterion when trading S&P 500 futures and crude oil futures, respectively. This suggests that stopping losses *together* with optimal leverage can have a substantial effect on long-run profit. Further, we find the perhaps counterintuitive result that stops placed very close to the entry price increase long-run profit dramatically, even if it results in a large number of whipsaws. The findings of this paper suggest that traders may have a lot to gain from determining leverage and stop order placement jointly when markets trend, and that profit maximizing traders should not necessarily be afraid of whipsaws.

By using the full sample of observations to calculate the returns of the trading strategy, we assume that the trader *a priori* knows the returns probability density function when applying leverage. This can be seen as a limitation to this study as we may oversimplify the complexity of actual trading out-of-sample as possibly nonstationary processes of prices are involved. However, as we evaluate the Vince criterion based on the same assumption, we expect the large relative profit difference between the stopping of losses and Vince criteria to remain relatively unchanged if we were to trade out-of-sample.

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On the Nature and Core Implications of the Dow Theory

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Abstract

The Dow Theory is not, as generally taken for granted by many people, just a simple technical analysis theory. Nor is it a mere momentum strategy, as suggested by some financial pundits. It is in reality a system of scientific thoughts on the stock market encompassing the stock market functions, the stock market pricing mechanism, and the stock price behavior and investment strategies, along with other important issues associated with the stock market.

In essence, the Dow Theory constitutes the judgement on the stock market pricing. The core implications of the Dow Theory are divisible into three parts, viz. the Dow Theory judgements on the stock market pricing, the stock market functions, and the stock price behavior, respectively. Among these three components, the Dow Theory judgements on the stock market pricing and the stock market functions are considered to be the real quintessence of the Dow Theory.

Introduction

This is the business of the stock market. It has to consider both basic values and prospects…In the long run, values make prices.
—— Charles H. Dow and William Peter Hamilton

The purpose of this research paper[1] is to draw the attention of the financial academic circles, the financial investment management circles, and the technical analyst industry to the latest research results of the Dow Theory on the part of the present author. At the same time, the author wishes to appeal to the financial academic circles, the financial investment management circles, and the technical analyst industry to launch a review of the scientific connotations of the Dow Theory so that a renewed reinterpretation of the theory can be made.

The present paper uses *The Stock Market Barometer*, by William Peter Hamilton, as the main object of analysis with *The Dow Theory*, by Robert Rhea, and *The ABC of Stock Speculation,* by S. A. Nelson, as the supporting objects of analysis.[2] For the sake of convenience and avoidance of ambiguity, this paper shall refer the foregoing *The Dow Theory* by William Peter Hamilton as the Dow Theory or Hamilton version of the Dow Theory, and *The Dow Theory* by Robert Rhea as Rhea version of the Dow Theory. The conclusion of this paper outlines the following:

(i) From the point of the view of the content, the Dow Theory is not, as generally taken for granted by many people, just a simple technical analysis theory. Nor is it a mere momentum strategy as endorsed by some financial scholars.[3] It is in reality a system of scientific thoughts on the stock market encompassing the stock market functions, the stock market pricing mechanism, and the stock price behavior and investment strategies, along with other important issues associated with the stock market. The technical analysis theory and momentum strategy only constitute part of the Dow Theory judgement on the stock price behavior.

(ii) In essence, the Dow Theory constitutes the judgement on the stock market pricing. The core implications of the Dow Theory can be divided into three parts, viz. the Dow Theory judgement concerning the stock market pricing, the Dow Theory judgement on the stock market functions, and the Dow Theory judgement on the stock price behavior. Among these three parts, the Dow Theory judgements relating to the stock market pricing and the stock market functions constitute the real quintessence of the Dow Theory.

(iii) From the standpoint of importance, the most important and quintessential parts of the Hamilton version have not been handed down by the Rhea version—effectively amounting to a loss of communication. Currently, the Dow Theory that we have access to is the Rhea version of the Dow Theory, which is based on a deletion and systematic integration of the Hamilton version of the Dow Theory. From a content point of view, the Rhea version amounts to roughly 50% of the Hamilton version.

This paper is arranged in the following way: apart from the Introduction dealing with an overview of the paper, subsequent sections delve into the scientific thoughts on the stock market functions associated with the Dow Theory; an examination of the assertions of the Dow Theory concerning the stock price behavior and Rhea version of the Dow Theory; an analysis of the scientific connotations and weaknesses of the Dow Theory; and concluding remarks on the paper.

Scientific Thoughts of the Dow Theory on the Stock Market Functions

The Dow Theory is not, as generally taken for granted by many people, just a simple technical analysis theory. Nor is it a mere momentum strategy as endorsed by some financial scholars. It is in reality a system of scientific thoughts on the stock market encompassing the stock market functions, the mechanism of the stock market pricing, and the stock price behavior and investment strategies, along with other important issues associated with the stock market.

Assertions of the Dow Theory Concerning the Stock Market Pricing Mechanism

In substance, the Dow Theory provides assertions and judgements on the stock market pricing. The core implications of the Dow Theory can be divided into three parts, viz. the Dow Theory judgement on the stock market pricing, the Dow Theory judgement on the stock market functions, and the Dow Theory assertions on the stock price behavior. Among these three parts, the Dow Theory judgements on the stock market pricing and stock market functions constitute the real quintessence of the theory.

The Mechanism of the Stock Market Pricing

[Hamilton-page-8] writes: "the price movement represents the aggregate knowledge of Wall Street and, above all, its aggregated knowledge of coming events...; The market represents everything everybody knows, hopes, believes, anticipates."

[Hamilton-page-127] Explains: "The market movement reflects all the real knowledge available, and every day's trading sifts the wheat from the chaff. If the resultant showing of grain is poor, the market reflects the estimate of its value in lower prices. If the winnowing is good, prices advance long before the most industrious and up-to-date student of general business conditions can bushel up the residue and set it forth in his pictorial chart."

[Hamilton-page-182] further explains: "It has been said before that the stock market represents, in a crystallized form, the aggregate of all American knows about its own business, and, incidentally, about the business of its neighbors. When a man finds his jobbing trade or his factory showing a surplus he tends to invest that surplus in easily negotiable securities. If this improvement is general it is all reflected and anticipated in the market, for he can buy in July and carry on ample margin what he knows he can pay for outright when he divides profits at the end of the year. He does not wait till the end of the year, because he realizes that the knowledge he possesses in July will by that time have become common property, and will have been discounted in the price."

The Pricing Basis and Pricing Process of the Stock Market

[Hamilton-page-88-90] writes: "All adjustments of the prices of these stocks individually must primarily be based upon values. For all practical purposes the Stock Exchange is an open market, and the business of such a market is to adjust conflicting estimates to a common basis which is expressed in the price...The stock market does not make its adjustment in a day. But over a period...This is the business of the stock market. It has to consider both basic values and prospects...At the close of a major downward movement, a primary bear market, prices will have passed below the line of values...Conversely, a bull market starts with stocks much below their real values, certain to be helped in anticipation by the general improvement in the country's business which the stock markets foresee and discounts. In the long advance values will be gradually overtaken."

[Hamilton-page-92] explains in the following way: "Every scrap of intelligence and knowledge available, uninfluenced in any real degree by manipulation, has been brought to bear in the adjustment of the stock market prices. Reproduction value, real estate value, franchises, right of way, good will—everything else—have been brought into the free-market estimate in a way which no valuation committee appointed by Congress could ever attain...But the Stock Exchange price records the value from day to day, from month to month, from year to year, from bull market to bear market, from one of Jevons's cycle dates to another.

[Hamilton-page-99] asserts in a remarkable way: "In the long run values make prices."

The Dow Theory Points Out That the Investor Should Base Their Understanding of the Stock Price Behavior on the Stock Value and Take Their Investment Decisions Accordingly

[Hamilton-page-75] writes: "But it is a vital mistake to suppose that speculation in stocks (for the rise at least) is a sort of gamble in which no one can win unless there is an equivalent loss somebody else. There need be no such loss in a bull market."

[Hamilton-page-38] indicates: "The best way of reading the market is to read from the standpoint of values. The market is not like a balloon plunging hither and thither in the wind. As a whole, it represents a serious, well-considered effect on the part of far-sighted and well-informed men to adjust prices to such values as exist or which are expected to exist in the not too remote future..." In reading the market, therefore, the main point is to discover what a stock can be expected to be worth three months hence and then to see whether manipulators or investors are advancing the price of that stock toward those figures. It is often possible to read movements in the market very clearly in this way. To know value is to comprehend the meaning of movements in the market".

The assertions of the Dow Theory concerning the stock market pricing brought to light the following:

First and foremost, the most fundamental function of the stock market is to make reasonable pricing for the stocks based on all available information on hand, and that is known as the pricing function of the stock market. The economic barometer and price discovery functions touched on in the following sections of this paper are based on the pricing function of the stock market.

Secondly, the assertion of the Dow Theory concerning the stock pricing hinges on a key assumption or, in other words, the ideal market environment, making possible the assertion of the Dow Theory concerning the stock pricing is in a free, complete and ratio-of-stocks-well-distributed stock market, wherein changes in the economy are reflected quickly in the changes of the stock price, the stock pricing will truly reflect changes in the basic factors and market expectations.

Third, the stock pricing is based on two factors in the stock market, viz. the basic value of the stock and market expectations. The Dow Theory asserts that "in the long run values make prices. [4] That is to say, the Dow Theory believes that, in the relatively long-term stock pricing, the basic value of the stock is the determining factor of its pricing, with the basic value of the stock being more important than the market expectations.

As to how to evaluate the basic value of the stock, Nelson's work has drawn references from the Dow Theory to advance the following statement, although the Dow Theory has not elaborated on how to measure the market expectations.

According to [Nelson, Page 47–48]: "Value is determined by the margin of safety over dividends, the size and tendency of earnings: the soundness of the balance sheet and of operating methods, and general prospects for the future. This sounds rather complicated but is not especially difficult to work out.

For instance, a year ago we almost daily pointed out that earnings had greatly increased during the year past; the fixed charges had not increased, hence, the actual value of stocks had advanced while prices had in almost all cases declined. It was obvious that this could not last; that net earnings must decrease or prices advance. There were many stocks cheap on their earnings and this was easily a matter of demonstration…

In the long run, the prices of stocks adjust themselves to the return on the investment, and while this is not a safe guide at all times, it is a guide that never should be laid aside or overlooked. The tendency over a considerable length of time will always be toward values. Therefore, the outsider who by studying earning conditions can approach a fairly correct idea of value has a guide for his investments which will, as a whole, be found safe."

Lastly, the stock pricing cannot realistically be completed in a day but takes several days or even longer to complete. In fact, the Dow Theory divides stock pricing into three distinctive kinds, viz. daily pricing, secondary trend pricing, and primary trend pricing. In other words, the Dow Theory prescribes three kinds of stock pricing: short-term stock pricing, mid-term stock pricing, and long-term stock pricing. The focal point of the Dow Theory lies in the primary trend stock pricing, viz. the long-term stock pricing, as the former two kinds of stock pricing could be manipulated according to the Dow Theory.

Stock Market Pricing and Stock Price Manipulation

Based on the influences of the investor behavior on the stock market pricing, the Dow Theory divides the stock market participants into five categories, viz. speculator, investor, stock manipulator, financial institution, and government. Based on the Dow Theory, participants in the stock market pricing should only include the former four categories of investors, and the government should not exert any influences on the stock market pricing.

In light of the different nature of influences exerted by investor behavior on the stock market pricing, we can discover that the stock market speculator and investor are the price taker of the stock market pricing. The stock manipulator and financial institution are the recipient of the stock market pricing whilst, at the same time, they are price makers of the stock market pricing. The government is the pure stock price maker. In the former four categories of investors, the stock manipulators and financial institutions are the price takers of the stock market pricing and, at the same time, they are the price makers of the stock market pricing. As a result, the actual stock market pricing could be manipulated.

Due to the stock manipulator and financial institution being only able to manipulate individual stocks instead of all the stocks or, in other words, the entire stock market, plus the stock manipulator and financial institution being incapable of manipulating the stocks all the time, we should not find it difficult to understand why the Dow Theory claims that the stock market daily variance and secondary trend could be manipulated but that the primary trend of the stock market could not be manipulated.

The key link in the Dow Theory specifying that the stock market primary trend could not be manipulated is based on the assumption that the government should not exert any influences on the stock market pricing. Per the Dow Theory, government as the price maker of the stock market pricing should have zero influences on the stock market pricing in terms of contribution. This key assumption constitutes the premise and basis for the effective operation of the Dow Theory. For this reason, the Dow Theory creators warn us the following:

[Hamilton-p-218] writes: "If there is one lesson which should have been burned in upon the public mind in the past decade, it is that when government interferes with private enterprise, even where that enterprise is directed to the development of a public utility, it can do incalculable harm and very little good."

The Dow Theory creators use the assertions of the stock market pricing as the basis to advance the scientific thoughts on the assertions of the stock market functions and the knowability of the stock market behavior from a macro standpoint.

Scientific Thoughts of the Dow Theory on the Stock Market Functions

[Hamilton-page-40] writes: "The stock market is the barometer of the country's, and even of the world's, business, and the theory shows how to read it."

The Dow Theory points out that the stock market is the barometer of the country's economy. This all-important function serves as one of the main functions of the stock market. This particular assertion of the Dow Theory does not come from assumptions or subjective imagination on the part of the Dow Theory creators. Rather they are founded upon a scientific summing up of immaculate analysis of the close relationship between the stock price and national economy in terms of historical data on the part of the Dow Theory creators. Charles Dow mainly relied on this particular scientific thought in creatively establishing DJIA and DJRA and, through them (as a barometer of the stock market), analyzing the boom and gloom of the national economy.

The Dow Theory Describes the Price Discovery Function of the Stock Market

[Hamilton-page-40-42] writes: "The sum and tendency of the transactions in the Stock Exchange represent the sum of all of Wall Street's knowledge of the past, immediate and remote, applied to the discounting of the future. There is no need to add to the averages as some statisticians do, elaborate compilations of commodity price index numbers, bank clearings, fluctuations in exchange, volume of domestic and foreign trade, or anything else. Wall Street considers all these things. It properly regards them as experience of the past, if only of the immediate past, to be used for estimating the future."

In the price movements, as Dow correctly saw, the sum of every scrap of knowledge available to Wall Street is reflected as far ahead as the clearest vision Wall Street can see. The market is not saying what the condition of business is today. It is saying what that condition will be months ahead. Even with manipulation, embracing not one but several leading stocks, the market is saying the same thing, and is bigger than the manipulation.

Under the Dow Theory, apart from fulfilling the function of the barometer of the country's economic situation, another important function of the stock market is its price discovery function, viz. in parallel with reflecting changes in the country's economy, it outlines expectations of changes of the future economy of the country and its own changes of the stock market in the future in advance, to the fullest possible extent.

The Assertion of the Dow Theory Concerning the Rules of the Movement of the Stock Market in Terms of Applicability and Knowability

First of all, the Dow Theory advocates that the price discovery function and the rules of movement are the common features inherent to the stock market and that such features will not vary with the passage of time.

[Hamilton-page-14-15] writes: "The law that governs the movement of the stock market, formulated here, would be equally true of the London Stock Exchange, the Paris Bourse or even the Berlin Boerse...The principles underlying that law would be true if those Stock Exchanges and ours were wiped out of existence. They would come into operation again, automatically and inevitably, with the re-establishment of a free market in securities in any great capital...But the stock market there would have the same quality of forecast which the New York market has if similar data were available...It would be possible to compile from the London Stock Exchange list two or more representative groups of stocks and show their primary, their secondary and their daily movements over the period of years...Average made."

Second of all, the Dow Theory advocates that the movement of the stock market has its inherent rules and that such rules are knowable.

[Hamilton-page-58-59] writes: "Order is Heaven's first law."

If Wall Street is the general reservoir for the collection of the country's tiny streams of liquid capital, it is the clearinghouse for all the tiny contributions to the sum of facts of business. It cannot be too often repeated that the stock market movement represents the deductions from the accumulation of that truth, including the facts on building and real estate, bank clearings, business failures, money conditions, foreign trade, god movements, commodity prices, investment markets, crop conditions, railroad conditions, political factors and social conditions, but all of these with an almost limitless number of other things, each having its tiny trickle of stock market effect.

There must be laws governing these things, and it is our present purpose to see if we cannot formulate them usefully... But we shall all recognize that order is Heaven's first law, and that organized society, in the Stock Exchange or elsewhere, will tend to obey that law even if the unaided individual intelligence is not great enough to grasp it.

Irrespective of the stock market fulfilling its function as the barometer of the country's economic performance or its price discovery function, these main functions are at the end of the day the results of the investor behavior. If the investor behavior follows certain patterns, the human society (collective investor behavior) behavior has definite rules to follow. In recognition of this, the movement of the stock market has its own rules to follow which are knowable. Such great thoughts of the Dow Theory stem from the profound understanding and mastery on the part of its creator of the actual stock price behavior and real humanity along with their interrelationship.

Assertions of the Dow Theory on the Stock Price Behavior

The Dow Theory uses the assertions of the stock market pricing as its basis in laying out practical rules on describing and predicting the stock price behavior from a micro point of view.

The Dow Theory Precisely Describes the Patterns of the Movement in the Stock Market

Movement in the stock market can be divided into three kinds of movement, namely, primary movement, secondary movement, and daily variation.

Based on [Hamilton-page-4-6], the Dow Theory is fundamentally simple. He showed that there are, simultaneously, three movements in progress in the stock market. The major is the primary movement...It will be shown that this primary movement tends to run over a period of at least a year and is generally much longer. Coincident with it, or in the course of it, is Dow's secondary movement, represented by sharp rallies in a primary bear market and sharp reactions in a primary bull market...Concurrently with the primary and secondary movement of the market, and constant throughout, there obviously was, as Dow pointed out, the underlying fluctuation from day to day.

[Hamilton-page-23] writes: "He was too cautious to come out with a flat dogmatic statement of his theory, however sound it was and however close and clear his reasoning might be...in the Review and Outlook of the Wall Street Journal of January 4, 1902, he says: 'Nothing is more certain that the market has three well defined movements which fit into each other. The first is the daily variation due to local causes and the balance of buying or selling at that particular time. The secondary movement covers a period ranging from ten days to sixty days, averaging probably between thirty to forty days. The third swing is the great move covering from four to six years'".

[Hamilton-page-23-24] comments: "Remember that Dow wrote this twenty years ago, and that he had not the records for analysis of the market movement which are now available. The extent of the primary movement, as given in this quotation, is proved to be far too long by subsequent experience; and a careful examination has shown me that the major swing before Dow wrote was never 'from four to six years,' rarely three years and oftener less than two. But Dow always had a reason for what he said, and his intellectual honestly assures those who knew him that it was at least an arguable reason."

The Dow Theory Accurately Points Out the Long-Term Upward Trend of the Stock Market and That Such Upward Trend Is Not Equal to the Downward Trend of the Stock Market

[Hamilton-page-147] writes: "So true is it that Wall Street is normally and healthily bullish...When we studied the major swings we saw that bull markets last longer than bear markets, and we might have seen that over a period of years long enough to average both bull and bear swings the tendency seems upward, or at least has heretofore advanced, with the growing wealth of the country."

[Hamilton-page-123] writes: "Among the many things which our stock market averages prove, one stands out clearly. It is that so far as the price movement is concerned, action and reaction are not equal. We do not have an instance of a bull market offset in the extent of its advance by an exactly corresponding decline in a bear market...We have seen that bull markets are, as a rule, of materially longer duration than bear markets. There is no automatically balancing equation there. I do not believe there is such an equation in human affairs anywhere."

The Dow Theory Succinctly Represents the Bull and Bear Markets

[Hamilton-page-32] writes: "It is a bull period as long as the average of one high point exceeds that of previous high points. It is a bear period when the low point becomes lower than the previous low points."

The Dow Theory correctly represents the connection between the amount of trading and the stock price trend.

[Hamilton-page-136] explains that "it is worthwhile to note here that the volume of trading is always larger in a bull market than in a bear market. It expands as prices go up and contracts as they decline." Later generations capture the meaning of the Dow Theory in this regard in one single sentence: "Volume Goes with the Trend."

The Dow Theory succinctly points out the absolute importance of closing price of the stock market in analyzing the stock market behavior. This is what later generations describe as that only closing prices are used. The appendix [Hamilton-page-288] points out that "the averages are compiled from closing prices. In case there is no sale of a particular stock, the last previous close is used."

The Dow Theory Emphasizes That the Two Averages Must Confirm

No one would negate the inherent scientific nature of the thoughts conceived by Charles H. Dow, viz. through analysis of the behavior of the stock indexes associated with several key representative sectors of the national economy, we are able to analyze the ups and downs associated with the economic activities. How then is it possible to enable the stock market barometer to accurately predict the trend of the economic movement? The Dow Theory provides an answer to this particular question through the establishment of DJIA and DJRA, and analyzes their common movement trends with a view to predicting success or failure of the involved economic activities. The Dow Theory lays repeated emphasis on the following key point: the two averages must confirm.

[Hamilton-page-185] comments that "our two averages of railroad and industrial stocks must confirm each other to give weight at any inference drawn from the price movement. The history of the stock markets shown by these averages, going back many years, proves conclusively that the two averages move together."

The Rhea Version of the Dow Theory

As a successor and proponent of the Dow Theory, Robert Rhea changed the direction of the research of Charles Dow and William Peter Hamilton. On this basis, he initiated a systemization of the Dow Theory to formulate his own version of the Dow Theory. Hugh Bancroft writes, "Mr. Rhea, after a carefully study of Dow's and Hamilton's writings (there were 252 editorials to be analyzed), has performed a valuable service in presenting the Dow Theory in a form to serve the individual investors or speculator."

Robert Rhea summarized 15 basic principles and expounded on each of them in relation to the stock price behavior described in the Hamilton version of the Dow Theory. These principles are: 1) Manipulation; 2) The Averages Discount Everything; 3) The Theory Is Not Infallible; 4) Dow's Three Movements; 5) Primary Movements; 6) Primary Bear Markets; 7) Primary Bull Markets; 8) Secondary Reactions; 9) Daily Fluctuations; 10) Both Averages Must Confirm; 11) Determining the Trend; 12) Lines; 13) The Relation of Volume to Price Movements; 14) Double Tops and Double Bottoms; 15) Individual Stocks. In addition, Robert Rhea's version has added two dedicated sections on "Speculation" and "Stock Market Philosophy," which are closely bound up with the Dow Theory.

A comparison between the Rhea and Hamilton versions of the Dow Theory in relation to the stock price behavior tells us that the Rhea version only focuses on the assertions of the Dow Theory concerning the stock price behavior on the part of the Hamilton version in terms of systemization, whereas the scientific thoughts of the Dow Theory concerning stock market functions and stock market pricing associated with the Hamilton version has been basically neglected by Robert Rhea. The Rhea version uses one basic tenet to replace the foregoing two omitted core implications of the Dow Theory, which is known as the famous statement of "The Averages discount everything." Consequently, the Rhea version of the Dow Theory is essentially the systemized assertion of the stock price behavior contained in the Hamilton version plus the above said famous statement.

Later advocates of the Dow Theory after Robert Rhea, such as Richard Schabacker, Robert D. Edwards, and John Magee, have chosen to follow the Rhea version of the Dow Theory instead of the Hamilton version. In the wake of Robert D. Edwards and John Magee having systematically used stock charts to analyze stock indexes and individual stock prices, the Rhea version of the Dow Theory and stock charts analysis have jointly constituted the classical technical analysis theory.

The Dow Theory's Scientific Connotations and Weakness

Scientific Connotations of the Dow Theory

First of all, the scientific connotations of the Dow Theory lie in the following: The Dow Theory accurately describes the real stock market pricing mechanism of the stock markets and captures the real stock market functions. It also graphically describes the rules of the movement in the stock price, and miraculously represents the interrelationship among the trio of actual stock behavior, the actual investor behavior and the basic factors in the economy. Precisely for this reason, the Dow Theory not only constitutes the cornerstone of the technical analysis theory, but also lays down the core theoretical foundation of the new stock market pricing theory in the future.

Secondly, the scientific nature of the Dow Theory is attributable to its two founders' decades of nonstop keen observation and profound study of the relationship between the stock market and the economy together with the changeover of the bull/bear markets. It is also attributed to the two founders' deep understanding of the strong influences exerted by the behavior of the actual investor, the market speculator, the manipulator, the financial institution and government with regard to the stock market pricing. Indeed, this has been a textbook example of the adage that real knowledge comes from practice.

Thirdly, if we link the scientific thoughts of the Dow Theory concerning the stock market with the modern financial history, we can find: Charles H. Dow was the first person to have correctly described the stock market functions, the first person to have correctly captured the mechanism of the stock market pricing, the first person to have precisely described the rules of the movement of the stock market and the first person to have put into place the stock market barometer in the financial history of the world.

What deserves special mention is that, over 100 years ago, Charles Dow and William Hamilton faced a dire lack of stock market data in conducting their research, and had no access to research papers concerning the stock pricing and stock price behavior for reference. Consequently, these two geniuses deserve any praise for their excellent work.

Weakness of the Dow Theory

Although the Dow Theory has formulated systematic scientific thoughts on the stock market (Macro portion) and rules describing the stock price behavior (micro portion), it has never been able to quantify, in a scientific manner, its thoughts on the stock market. Nor has it ever been able to scientifically quantify its rules describing the stock price behavior. If we ever view the stock market behavior as a whole, the Dow Theory has only completed about 40% of the entire stock market research workload. The remaining 60% relating to quantifying the scientific thoughts on the stock market and the formulation of the models describing the inner mechanism and rules of the stock market movement from the angle of microstructure of the stock market, and to further evolve and extend the Dow Theory (if needed) on the foregoing basis, has been left to be accomplished by future generations.

Obviously, the Dow Theory is a stock market pricing theory that requires further refinement and upgrades, as appropriate.

As the Dow Theory has been unable to formulate models to quantify the inner mechanism and rules of the stock price movement from the angle of microstructure of the stock market, the Dow Theory's shortcomings in describing the stock price behavior are apparent. For instance, certain Dow Theory statements on the stock price behavior address only the symptoms rather than the root cause of the issue. Even though some statements have turned out to be very accurate, the Dow Theory simply fails to tell us why they were so accurate in the first place. As the symptoms of the stock price behavior vary significantly, it is not at all surprising that investors would invariably experience difficulties and inadequacies with the Dow Theory in terms of operability over a short span of time.

To scientifically understand and comprehend the stock market functions, the stock market pricing and the stock market behavior etc., people must have a comprehensive scientific cognition and understanding of actual investor behavior and stock price behavior together with their interrelationship. Such requirements are clearly too advanced, far exceeding the confines of the times when the Dow Theory founders carried out the research. In fact, it is too much to ask for full resolutions of such matters from the financial academic circles, even at the present time.

The Dow Theory Being Ignored by the Financial Academic Circle

Almost in parallel with the unveiling of the Rhea version of the Dow Theory, in 1934, Alfred Cowles published his "Can stock market forecasters forecast?" paper in the journal *Econometrica*. In the paper (page 315), Cowles states:

"From December 1903 to December 1929, Hamilton, through the application of his forecasts to the stocks composing the Dow Jones industrial averages, would have earned a return, including dividend and interest income, of 12 percent per annum. In the same period, the stocks composing the industrial averages showed a return of 15.5 percent per annum. Hamilton, therefore, failed by an appreciable margin to gain as much through his forecasting as he would have made by a continuous outright investment in the stocks composing the industrial averages."

In the summary of the paper, he writes the following:

"William Peter Hamilton, editor of the Wall Street Journal, publishing forecasts of the stock market based on the Dow Theory over a period of 26 years, from 1904 to 1929, inclusive, achieved a result better than what would ordinarily be regarded as a normal investment return, but poorer than the result of a continuous outright investment in representative common stocks for this period. On 90 occasions, he announced changes in the outlook for the market. Forty-five of these predictions were successful and 45 unsuccessful."

Although technical analysis and fundamental analysis were well received and extensively applied by Wall Street, as from Cowles (1934) testing of the Dow Theory providing strong evidence against the ability of Hamilton, the most famous Wall Street technician, to forecast the stock market, technical analysis had not been acceptable to the financial academic circles ever since. 64 years later, the Brown, Goetzmann and Kumar (1998) paper completely overturned the Cowles (1934) research conclusions. The paper concludes:

"A review of the evidence against William Peter Hamilton's timing abilities suggest just the opposite—his application of the Dow Theory appears to have yielded positive risk-adjusted return over a 27-year period at the beginning of the century. The basis of the track record seems to have been his ability to forecast bull and bear market moves...Ever since, Cowles' article 'Chartists' in general, and Dow theorists in particular, have been regarded by financial economists with skepticism. Our replication of Cowles' analysis results contrary to Cowles' conclusions. At the very least, it suggests that more detailed analysis of the Hamilton version of the Dow Theory is warranted."

Because the financial academic circle only regards the Dow Theory as a simple technical analysis theory or a mere momentum strategy as the object of research, even though the Brown, Goetzmann and Kumar (1998) paper proved that the Dow Theory was capable of predicting the market, the paper was given little attention in the financial academic circle, which it well deserved. In fact, the prejudice and spite against the Dow Theory on the part of the financial academic community had not been changed and eliminated by the Brown, Goetzmann and Kumar (1998) paper. At the same time, such scientific conclusions as the Dow Theory regarding the stock market functions and the stock market pricing mechanism have been simply ignored or taken lightly by the financial academic circle in general.

Conclusion

It is said that the great scientist Isaac Newton (big loser of the South Sea Stock Price Bubble) muttered that he "could calculate the motions of the heavenly bodies, but not the madness of the people." Over the past 100 years, the stock market barometer[5] created by Charles Dow not only successfully measured the relationship between the stock market and the economy, but also successfully measured the madness and desperation on the part of the investors caught up in the bull and bear turbulences of the stock market.

Due to the above-mentioned technical difficulties and inclement technical analyst industrial environment, there have been severe deviations and even stoppages in the effort to carry forward and extend the Dow Theory in terms of scientific thoughts and research directed in a scientific manner all along. With the passage of time, the Dow Theory assertions on the stock market functions and stock market pricing—which may be even greater scientific thoughts than the stock market barometer—have been neglected and forgotten. The Rhea version of the Dow Theory that has been handed down to the present has already replaced the Hamilton version of the Dow Theory as the authoritative Dow Theory that is prevailing in the world at this point in time.

When Robert Rhea made simplification and systemization of the Dow Theory, he could never have imagined that "the averages discount everything" mantra could never replace the Dow Theory scientific conclusions on the stock market functions and stock pricing mechanism. As a result, the above said mantra basically became an empty shell without any substance. Moreover, Robert Rhea could never have imagined that, in parallel with the reduction and deletion of such scientific conclusions, he had inadvertently deleted the theoretical basis of the Dow Theory on the stock price behavior. Consequently, a sad fact remains that, while the Rhea versions of the Dow Theory and Robert D. Edwards and John Magee's stock chart analysis techniques jointly constitute the classical technical analysis theory, the real scientific theoretical foundation in support of the classical technical analysis theory has ceased to exist.

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Notes

[1] The present paper is the second one of the series, of research papers dealing with traditional technical analysis theories. The first report of the series entitled "On the Great Dow Theory," had been accepted by the *IFTA Journal* for publication in its 2019 annual edition. This research project is aimed at the conduct of a scientific evaluation and comprehensive revision of the traditional technical analysis theories.

[2] The present paper has drawn references of a significant number of sentences and paragraphs from *The Stock Market Barometer.* The author therefore wishes to express his profound gratitude to the copyright owner of the book, John Wiley & Sons, Inc.

[3] Brown, Goetzmann and Kumar (1998) thinks that the Dow Theory should be regarded as a Momentum strategy.

[4] The Great Buffett has mentioned time and again that, from a relatively long-term point of view, the basic value of the stock determines the stock price. People invariably believe that he is quoting his coach Graham or re-stating the viewpoint of Williams, the founding father of fundamental analysis. It has not occurred to anyone that this insightful viewpoint actually comes from the Dow Theory.

[5] DJIA conceived by Charles H. Dow in 1884 as the well-known economic leading indicator has witnessed a rise from 40 points to about 25,000 points today.

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The Coherent Market Portfolio

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Abstract

The starting point of this work is the Modern Portfolio Theory of Markowitz and Sharpe, who originated the term *market portfolio*. They used the standard deviation to measure risk—an approach that is no longer up to date since Artzner, Dealbaen, Eber and Heath introduced the *coherent measures of risk*. Therefore, the present work uses a coherent risk measure to define a coherent market portfolio. Another criticism of Modern Portfolio Theory is that there is no specification to estimate the yield of securities. In this work, this shortcoming is eliminated by means of technical analysis, and the expected return will be rated by the well-known motto "The trend is your friend." The backtest of the constructed portfolio in the European and American markets shows that this theoretical work also provides a practical added value.

Introduction

The "Modern Portfolio Theory" is based on the work *Portfolio Selection* by Harry Markowitz (1952), which addresses the problem of composing an optimal portfolio. It is assumed that there are only risky assets and that the optimal portfolio for an investor is dependent on its risk-return preference. Based on this approach, William Sharpe (1964) has defined a so-called *market portfolio* by introducing a money market investment. This market portfolio is independent of an investor's preference and maximizes the Sharpe ratio. As a consequence, the investor preference decides only in the weighting between the investment in the money market and the market portfolio. This historical result is recapitulated in the "Modern Portfolio Theory" section, since it is the basis for this paper.

The pioneering research by Harry Markowitz and William Sharpe was honored with the Nobel Prize for Economic Sciences in 1990, donated by the Swedish Central Bank, together with Merton Miller. Nonetheless, the assumptions on which the model of Markowitz is based on are quite controversial. Its prerequisites are, firstly, that every investment has an expected return and that the standard deviation of that return is known and secondly, the standard deviation of the return serves as a risk indicator in its model. However, these assumptions are questioned in practice. On the one hand, it is unclear how to estimate the expected return of a security, and on the other hand, a standard deviation also includes advantageous fluctuations and thus, does not necessarily serve as a measure of risk. For both assumptions, alternatives are offered in this paper.

To define suitable risk measures, Artzner, Delbaen, Eber and Heath established *coherent measures of risk* (1999). Their definition of a suitable risk measure is explained in the "Coherent Measures of Risk" section. As an example of a coherent measure of risk, the expected shortfall and its calculation are also introduced. On this basis, the risk measurement is performed in the following sections.

Of course, to estimate future returns on a security, technical analysis is getting involved. One of the basic principles of technical analysis is "The trend is your friend." In the "A Trend-Following Approach to Estimate Future Returns" section, this motto is the basis for two fairly simple procedures: the use of rate-of-change or the use of a linear regression. The advantage of the chosen approaches is that they easily enable back testing. Nonetheless, more complex methods for estimating the return on a security are also conceivable.

Using a coherent and hence better risk measurement as well as a successful estimation of future returns using the technical analysis, the previously presented Modern Portfolio Theory will be revised. In "The Coherent Market Portfolio" section, a new *market portfolio* will be established that is based on a *coherent* measure of risk and is therefore called a *coherent market portfolio.*

The practical use of these theoretical papers is demonstrated in the "A Trading System Based on the Coherent Market Portfolio" section, a trading strategy based on the coherent market portfolio will be presented. This strategy is back-tested on the European as well as on the American stock market. A short summary in the Conclusion completes the work.

Modern Portfolio Theory

The Efficient Frontier Without Restrictions

Model Setup

In the basic setup of the Modern Portfolio Theory, there are N securities, each of them has a known expected return r_i. However, this return is uncertain for all securities and its standard derivation is quantified with σ_i. Furthermore, the returns of the securities are correlated and the covariance matrix of the returns is given by $C_{ij} = \sigma_i \sigma_{ji} \rho_{ij}$, where ρ_{ij} denotes the correlation between security number i and security number j. Obviously, the matrix C is symmetric and it is assumed that is invertible—hence, each security comprises a certain idiosyncratic risk that cannot be eliminated with linear combinations of other securities. So, in this model, there is no deterministic[1] investment possible.

The composition of a portfolio is described by weights w_i, which denotes the portion of the security i in the portfolio. Hence, there is the constraint[2]

$$\sum_{i=1}^{N} w_i = 1 = 1^T w \qquad (1)$$

The expected R return of such a portfolio is given by:

$$R = \sum_{i=1}^{N} w_i r_i = r^T w \tag{2}$$

and the variance V of the portfolio return is evaluated by:

$$V = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij} w_i w_j = w^T C w$$

The standard derivation of the portfolio's return is simply given by $\sqrt{V}$, which is interpreted as the risk of this portfolio.

Mathematical Solution

In this environment, the search for the composition of a portfolio with the lowest possible risk is performed under the condition that this portfolio has an expected return of R. From the mathematical point of view, this is the problem of minimization of $\sqrt{V}$, the risk of the portfolio, under the constraints (1) and (2). Instead of minimizing $\sqrt{V}$, this problem is obviously equivalent to minimize ½V. The standard approach to solve such an optimization under constraints is the method of Lagrange multipliers. The Lagrangian of this problem is given by:

$$L(w, \lambda, \mu) = \tfrac{1}{2} w^T C w + \lambda (R - r^T w) + \mu (1 - 1^T w)$$

The necessary condition for the solution is that all partial derivations of the Lagrangian are zero:

$$0 = C w - \lambda r - \mu 1$$

$$0 = R - r^T w$$

$$0 = 1 - 1^T w$$

The first equation yields the portfolio decomposition expressed by the two Lagrange multipliers:

$$w = \lambda C^{-1} r + \mu r^T C^{-1} 1 \tag{3}$$

Inserting this solution into the second and third equation yields a system of two linear equations for λ and μ:

$$\lambda \; r^T C^{-1} r + \mu r^T C^{-1} 1 = R$$

$$\lambda \; 1^T C^{-1} r + \mu 1^T C^{-1} 1 = 1$$

Using the abbreviations $a = r^T C^{-1} r$, $b = r^T C^{-1} 1$, $d = 1^T C^{-1} 1$, and using the fact that the matrix C^{-1} is symmetric, hence $b = 1^T C^{-1} r$, one can obtain the solution for the two Lagrange multipliers by:

$$\begin{pmatrix} \lambda \\ \mu \end{pmatrix} = \frac{1}{a\,d - b^2} \begin{pmatrix} d & -b \\ -b & a \end{pmatrix} \begin{pmatrix} R \\ 1 \end{pmatrix}$$

Since λ and μ are known by this equation now, also the composition of the portfolio that minimizes the variance for a given expected return is explicitly given by equation (3). Also, the variance can easily be computed in terms of the expected return of the portfolio:

$$V(R) = w^T C w = a \lambda^2 (R) + 2 b \lambda(R) \mu(R) + d \; \mu^2 (R)$$

Since $\lambda(R)$ and $\mu(R)$ are linear in R, the minimal variance $V(R)$ of a portfolio with expected return R shapes a quadratic parabola.

Example

To illustrate the previous computations, we consider an example of four stocks and assume that there is a constant pairwise correlation between these assets of 60%. Their expected returns and volatilities are listed in Table 1.

Table 1. Expected Returns and Variance of the Equities in the Example

Security	Expected Return	Variance of the Return	Risk (standard derivation)
Equity 1	4%	15%	0,3872
Equity 2	5%	20%	0,4472
Equity 3	3%	20%	0,4472
Equity 4	6%	30%	0,5477

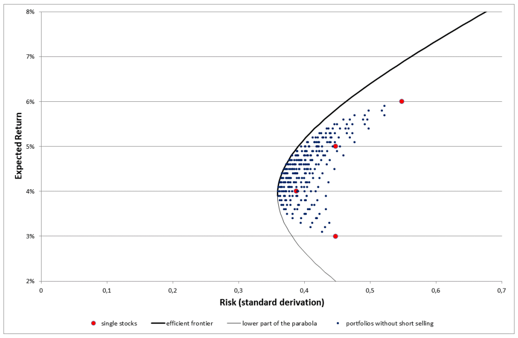
Given this example, the results of the previous calculations are shown in Figure 1. The red dots show the single stocks available for investing. The black line shows the minimal risk of an optimal portfolio for each given return, hence the function $\sqrt{V(R)}$. This curve is to the left of the individual shares, which underlines the statement that diversification can reduce the risk compared to a single investment. The top branch of the black curve is called *efficiency frontier* because all efficient portfolios lie on this line (i.e., the portfolios with the minimum risk for a given expected return). An investor will invest in a portfolio that is located at the efficiency frontier, and the concrete selection is based on his personal risk appetite.

The Model in the Absence of Short Selling

In the previous analysis, there was no restriction on the portfolio composition. Following the discussion of Markowitz, 1952, one can consider the restriction that there is no possibility of short selling, and the mathematical description of this restriction is given by $w_i \geq 0$. Using this additional condition, there is no closed form solution available, and one needs numerical solutions to determine the variance minimizing portfolios and the corresponding efficient frontier.

To illustrate the results under the no-short-selling constraint, the above example is revisited under this constraint. The various risk-return profiles of portfolios with no short positions are shown with blue dots in Figure 1. This graph shows that one has to take significantly higher risks to construct a portfolio with an expected return of nearly 6%, and one cannot expect to construct a portfolio with an expected return above 6% in this example.

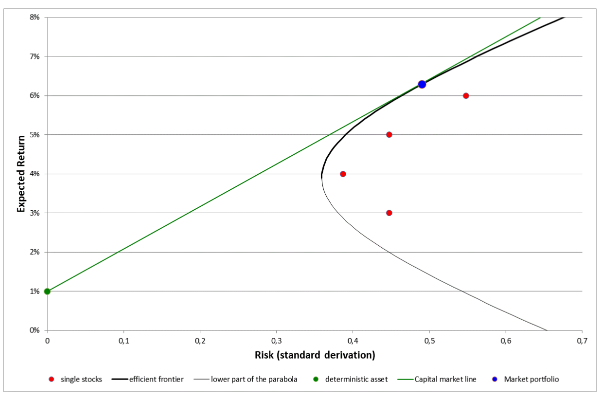
Figure 1. The Efficient Frontier and the Portfolios Without Shortselling



The Sharpe-Ratio and the Market Portfolio

William Sharpe (1964) expanded the universe on investment opportunities by introducing the possibility of investing in a fixed-term deposit with rate r_0. The introduction of such a deterministic investment has an important consequence, which is explained by Figure 2. From the risk-bearing securities (red dots), a portfolio with minimal risk (standard deviation) can be composed for every expected return according to the previous results. The optimal portfolios lie on the efficiency frontier, which is again shown as a black curve. Furthermore, there is now a deterministic investment that promises a certain secure return. This is marked in the figure with a green dot and lies exactly on the yield axis since its return has a zero variance. Using this picture, one can define the *Capital Market Line* (green), which goes through the deterministic asset (green dot) and which is tangent to the efficiency frontier (black line). The touching point (blue dot) is called either *Tangency Portfolio or Market Portfolio.*

Figure 2. Portfolio Selection Including a Deterministic Asset



The capital market line represents all portfolios that are obtainable by mixing the market portfolio (MP, blue dot) and the deterministic asset (DA, green dot). Let $\omega \in [0,1]$ and r_{MP} the expected return σ_{MP} and the risk of PM and study a combined Portfolio $P(\omega) = \omega MP + (1-\omega)\, DA$. The expected return and the standard derivation of this portfolio is given by

$$\textit{expected Return}\ (P(\omega)) = \omega r_{MP} + (1-\omega)\, r_0 = r_0 + \omega(r_{MP} - r_0)$$

$$\text{standard derivation}\ (P(\omega)) = \omega\sigma_{MP}$$

Hence, both the risk and the yield of the portfolio mixed by the deterministic asset and the market portfolio are linear functions in ω, and hence, these portfolios lie on the green capital market line. It is clear that each of this $P(\omega)$ is preferred to any other portfolio: For a given risk level, the portfolio on the capital market line yields the largest return compared to any other portfolio.

From the last two equations, the slope S of the capital market line can be computed to

$$S = \frac{r_{MP} - r_0}{\sigma_{MP}}$$

This expression can also be computed for any other portfolio than the market portfolio MP and denoted the *Sharpe Ratio* of a portfolio. Hence the market portfolio MP can be characterized as the portfolio on the efficiency frontier which maximizes the *Sharpe Ratio.*

So, the market portfolio is independent from any investors risk preference. Each rational investor will invest into a mixture of the market portfolio and the deterministic asset, hence into $P(\omega)$. The mixture parameter is the only individual parameter for each investor, which has to be chosen in accordance to his individual risk preference.

Coherent Measures of Risk

The previous section presented the Modern Portfolio Theory based on the standard deviation as a risk measure. As explained in the introduction, this risk measurement methodology is controversial. Therefore, general considerations on risk measures are presented in this section. The essential inspiration for this is based on the work of Artzner, Delbaen, Eber and Heath (1999), who established the term of a *coherent risk measure*. The axiomatic approach of their work leads to a specific risk measure, the *Expected Shortfall*, and its calculation in practice is also presented. In light of the fact that the deterministic investment is of particular importance in portfolio theory, risk measurement using the deterministic investment as benchmark is also considered.

Definition of Coherent Measures of Risk

A general definition of *risk* based on an encyclopedia reads:

Risk is the possibility to suffer harm due to action or omission.

In the field of finance, the harm is given by a financial loss, and the action is the composition of a portfolio. Furthermore, the nature of the risk is characterized by uncertainty—a guaranteed loss is therefore no risk anymore! To model the uncertainty, a probability space (Ω, F, P) is introduced that describes, for example, all possible outcomes of future share prices. For the profit or loss, the portfolio is crucial, and L denotes the set of all loss functions, that is, the set of all mappings from Ω to R. A function $L \in \mathcal{L}$ indicates the loss (or in the case of a negative value the profit) that a portfolio suffers in a particular scenario. The risk for a certain loss function of a portfolio is denoted by ρ. Using these notations one can define according to (Artzner and others, 1999):

Definition (coherent measure of risk): A mapping $\rho: \mathcal{L} \rightarrow \mathbb{R} \cup \{+\infty\}$[3] is called a coherent measure of risk, if and only if these four axioms apply:

Positive homogeneity: For $\lambda \geq 0$ all $L \in \mathcal{L}$ and holds:

$$\rho(\lambda L) = \lambda \rho(L)$$

Monotonicity: For all $L_1, L_2 \in \mathcal{L}$ with $L_1 \leq L_2$ holds:

$$\rho(L_1) \leq \rho(L_2)$$

Subadditivity: For all $L_1, L_2 \in \mathcal{L}$ holds:

$$\rho(L_1 + L_2) \leq \rho(L_1) + \rho(L_2)$$

Translation invariance[4]**:** For all $\lambda \in \mathbb{R}$ and $L \in \mathcal{L}$ holds:

$$\rho(L + \lambda) = \rho(L) + \lambda$$

Hence, a coherent measure of risk fulfills four rules, which all have a practical interpretation:

1. The positive homogeneity states that, for example, if all positions in a given portfolio are doubled ($\lambda = 2$), such an enlarged portfolio bears twice the risk of the original portfolio. Thus, it is also clear that the risk is not measured as a relative change (*e.g.,* in percentage), but denotes an absolute size in a currency (*e.g.,* USD).
2. If there are two portfolios, and the loss in the first portfolio is always less or equal to the loss of a second portfolio, then the risk of the first portfolio should be smaller compared to the second portfolio. That is the statement of the monotonicity axiom.
3. The subadditivity axiom states the mathematical formulation of classical diversification: the overall risk that is made up of two portfolios should be less than or equal to the sum of the risks of the two individual portfolios.
4. The translation invariance covers the effect of additional in- or outflows on the risk of a portfolio: If there is an additional outflow $\lambda > 0$, this increases the risk, and an additional income $\lambda > 0$ reduces the risk of a portfolio accordingly.

Properties of Well-Known Risk Measures

In this section, three different risk measures are studied with respect to the four axioms of coherent risk measures. The proofs of the lemmas in this section are omitted, the mathematically interested reader will find all proofs in (Reiss, 2019). Mostly, only simple calculations are needed; harder to proof is the subadditivity of the expected shortfall, which is also given *e.g.,* in (McNeil and others, 2005) or (Embrechts and Wang, 2015).

Standard Derivation

In the Modern Portfolio Theory, the standard deviation serves as a measure of risk. It is not surprising that this risk measure fulfills the subadditivity—otherwise there would have been no diversification effect in the portfolio theory. However, the standard deviation is not a coherent measure of risk and thus the criticism in the use of standard deviation as a measure of risk is justified.

Lemma 1: The standard derivation is not coherent. It complies with positive homogeneity and subadditivity, but the standard derivation is neither monotone nor translation invariant.

Value at Risk

The *Value at Risk* is a well-known risk measure since it is the market-standard risk measure and is still used in banking supervision. It is defined as a quantile of the loss distribution for a given percentile α, and typical values for are 95% or 99%. To interpret this definition, the value at risk for 99% percentile states that in 99% of all cases, the loss of the portfolio will not exceed this threshold. However, there are two criticisms on this risk measure: At first, it does not say anything about the size of the losses, if they exceed the value at risk; hence, huge losses in the case of unlikely events are ignored. On the other hand, the value at risk does not fulfill the condition of subadditivity and is inappropriate to establish a limit system in a financial institution: Limiting the value at risk to all individual portfolios of a bank does not ensure that the value at risk of the bank is limited by the sum the individual portfolios value at risk.

Definition (value at risk): Let $L \in \mathcal{L}$ and $0 < \alpha < 1$. Then the value at risk for the percentile α is defined by

$$\mathrm{VaR}_\alpha(L) := \inf\{x \in \mathbb{R} \mid \mathbb{P}[L \leq x] \geq \alpha\}$$

Lemma 2: The value at risk fulfills the axioms of positive homogeneity, monotonicity and translation invariance. But, it is not subadditive and therefore not a coherent risk measure.

Expected Shortfall

Another risk measure is the *expected shortfall*. In contrast to the value-at-risk, the expected shortfall focuses on the worst $1 - \alpha$ percent of the scenarios, and the expected shortfall is defined as the expectation of the loss in these worst scenarios.

Definition (expected shortfall): Let $L \in \mathcal{L}$ and $0 < \alpha < 1$. Then the expected shortfall is given by

$$ES_\alpha(L) := \frac{1}{1-\alpha} \int_\alpha^1 VaR_p(L)\ dp$$

Lemma 3: The expected shortfall is a coherent risk measure, *i.e.,* it fulfills the four axioms positive homogeneity, monotonicity, subadditivity and translation invariance.

In the following sections of this paper the expected shortfall will serve as risk measure since it is coherent, and it is anticipated that this risk measure will become broadly accepted in the financial industry, even if the value at risk is still the standard risk measure today. In the longer term, it seems likely that the general use of the expected shortfall will prevail since the Basel Committee on Banking Supervision at the Bank for International Settlements recommends converting from value at risk to expected shortfall (2013).

At this point, a reference to other risk measures seems appropriate, namely the *worst conditional expectation* and the *tail conditional expectation;* the latter is also called *conditional value at risk*. The mathematical definitions are slightly different, and for an impressive example in which these risk measures lead to diverse results, see (Acerbi and Tasche, 2002). In particular, the *tail conditional expectation* and thus, the *conditional value at risk,* is not coherent.

Computing the Expected Shortfall in Practice

The expected shortfall as a coherent measure of risk has been presented theoretically, and in this section the methodology for practical calculation is presented. In this example, the risk horizon will be one week and the percentile used will be 95%. The basis for this computation is a historical simulation, which assumes that the securities behave the same over a certain period of time in the past. For the sake of simplicity, the risk measurement for a portfolio of equities or funds is considered, hence, a portfolio of securities without maturity. For securities with an explicit maturity, their behavior changes over time, and no similar behavior over a certain historical period may be assumed. Therefore, such securities require a more complex handling and are not considered here.

In institutional risk management, the historical simulation is based on time series with daily data. This general practice, however, involves a special effort for creating the time series since holidays in different countries or the time shift between different stock exchanges must be taken into account. To avoid these difficulties, a historical simulation based on weekly data is presented here. For all shares, the last 51 weekly closing prices are considered, which corresponds to a history of almost one year. For the i^{th} share, C_j^i denotes the closing price j weeks ago, hence for $j=1$ it is the last week closing price, for $j=2$ the close price at the second to last week, etc. Since the relative changes are relevant for the stocks, the changes are considered on a logarithmic scale:

$$\delta_j^i := \ln C_j^i - \ln C_{j+1}^i = \ln \frac{C_j^i}{C_{j+1}^i} \qquad \text{with } j = 1 \ldots 50$$

This definition for relative changes on a logarithmic scale is usual; using the well-known approximation $ln(1+x) \approx x$ one can easily show that the definition is close to the classical definition of relative changes:

$$\ln \frac{C_j^i}{C_{j+1}^i} = \ln \frac{C_{j+1}^i + C_j^i - C_{j+1}^i}{C_{j+1}^i} = \ln\left(1 + \frac{C_j^i - C_{j+1}^i}{C_{j+1}^i}\right) \approx \frac{C_j^i - C_{j+1}^i}{C_{j+1}^i}$$

Hence, the first 50 scenarios for the equities have been defined, but this number is too small for statistics, and therefore, an additional 50 scenarios are introduced by the technique of mirroring[5]:

$$\delta_{50+j}^i := \ln C_{j+1}^i - \ln C_j^i = -\,\delta_j^i \qquad \text{with } j = 1 \ldots 50$$

The use of mirrored scenarios is quite common and well known in practice (Holton, 2014); a detailed study further shows that the historical simulation with mirrored scenarios also provides better results for the computation of the expected shortfall (Zikovic and others, 2011). In addition to the increased number of scenarios, this approach has the advantage of having as many positive and negative scenarios, and thus a quantile $\alpha \geq 0$ of ensures that the expected shortfall of a stock does not become negative. Based on these 100 scenarios for the securities, the loss function of a portfolio can be evaluated. If the portfolio contains a total of N positions, and let n_i denote the number of share i in the portfolio and C_0^i the current share price, then:

$$L_j = \sum^{N} n_i\, C_0^i \left(1 - \exp(\delta_j^i)\right) \qquad \text{with } j = 1 \ldots 100$$

These values of L_j will be put in ascending order, thus, reordered values are denoted by $\tilde{L}$ and hence $j \leq k$ implies $\tilde{L}_j \leq \tilde{L}_k$. The expected shortfall results as the expectation beyond a confidence α. In our case, α=95%, and for a total of $S=100$ scenarios, 5 scenarios are outside the chosen confidence. In general, the expectation is computed by the K largest values with $K = (1-\alpha)\, S$, and the expected shortfall is given by:

$$\mathrm{ES}_\alpha = \frac{1}{K} \sum_{i=S-K+1}^{S} \tilde{L}_j$$

Measuring Risk With Respect to a Benchmark

The presented risk measurement of the expected shortfall can not only be considered in a nominal risk as in the previous section, but also with respect to a given benchmark. Then the loss function is calculated by the deviation from the benchmark. In the first case, an index is used for benchmarking, and the coherent risk measurement provides an alternative to the classical tracking error, which typically corresponds to a standard deviation. In the second case, the deterministic investment is considered a special case of a benchmark.

An Index as Benchmark

To determine the risk of a portfolio with respect to a benchmark (e.g., a stock index), one also needs to know the historical scenarios of the benchmark δ_j^B in addition to the historical scenarios of the stocks δ_j^i. These are determined analogously to the scenarios of the shares. Let B_j be the weekly close of the benchmark j weeks ago and define:

$$\delta_j^B := \ln B_j - \ln B_{j+1} \qquad \text{with } j = 1 \ldots 50$$

$$\delta_{50+j}^B := -\delta_j^B \qquad \text{with } j = 1 \ldots 50$$

Holding on the notations of the previous section, the loss in each scenario is now the underperformance with respect to the benchmark and hence given for j=1...100 by:

$$L_j := \left(\sum_{i=1}^{N} n_i C_0^i\right) \exp \delta_j^B - \sum_{i=1}^{N} n_i C_0^i \exp \delta_j^i \;=\; \sum_{i=1}^{N} n_i C_0^i \left(\exp \delta_j^B - \exp \delta_j^i\right)$$

In the case, that the benchmark is a constant, hence a nominal value, the variation of the benchmark vanishes, and this formula results in the equation of the “Computing the Expected Shortfall in Practice” section.

The Deterministic Asset as Benchmark

If the benchmark is the risk-free investment, then this investment has a deterministic payoff profile, and there is no reason to estimate the distribution of this investment. Accordingly, only the current risk-free interest rate r_0 and the time horizon of the risk measurement τ, which is always one week in this paper, are relevant. Hence the variation of the benchmark is given by

$$\delta_j^B := \ln(1 + r_0\, \tau) \;\approx r_0\, \tau \qquad \text{for } j = 1 \ldots 100$$

This value for δ_j^B does not change for the mirrored scenarios since the effect of the current risk-free investment is immediately obvious. Using the formulas of this section or the translation invariance axiom, one can show that an investment of an amount in the deterministic asset has a nominal risk of

$$ES_\alpha\,(\textit{deterministic investment}) = -\,A\, r_0\, \tau$$

If this risk calculation is carried out against the deterministic investment over a period corresponding to the risk horizon, then the expected shortfall is obviously 0. Such a portfolio always shows exactly the change in value of the benchmark, and in this interpretation, it is therefore risk-free. This consideration applies regardless of the sign of r_o and holds in particular also for negative interest rates.

A Trend-Following Approach to Estimate Future Returns

The Introduction pointed to two criticisms of the Modern Portfolio Theory. In addition to risk measurement based on variance, the development of portfolio theory has suggested that the yield on the securities can be estimated. However, this aspect has not been further investigated in the Modern Portfolio Theory. At this point, the technical analysis could provide additional insight. One central principle of our discipline says:

The trend is your friend!

Accordingly, the idea is to estimate future returns on a security based on its historical return. This is certainly the simplest way, and there are definitely more advanced methods available in technical analysis. But on the one hand, such a simple procedure easily allows one to implement a backtest of the strategy, and on the other hand, it is sufficient to beat the market, as the backtest will show in the "A Trading System Based on the Coherent Market Portfolio" section.

Estimation Based on Rate of Change

The rate of change (RoC) is computed based on the close of two days: The current price C_0 and the price C_T a certain period T ago. Throughout this work, the period T will be one year, hence the rate of change will serve as expected annual return.

$$RoC := \frac{C_0 - C_T}{C_T}$$

Estimation by Linear Regression

The above yield estimate is only based on the prices of two key dates and does not consider the price development during this year. In this respect, the simple idea can easily be improved by using a linear regression on the data to estimate the historical return of r a given stock. In this approach, the close prices of the stock should be approximated by the function $\exp(\lambda + rt)$. For the practical calculation, the price data of the stock of a certain period (for example, within 1 year) are used, these are denoted by C_{t_i}, with $i = 1 \ldots N$. To determine the regression, first the logarithm is calculated for this data. Let $X_i := \ln\, In\, C_{t_i}$, then there is a linear relationship $\lambda + rt$ assumed for this data. The position parameter λ is not relevant for the further analysis, and r can be calculated using the following equations. First, calculate the means $\bar{t} := \frac{1}{N}\sum_{i=1}^{N} t_i$ and $\bar{X} := \frac{1}{N}\sum_{i=1}^{N} X_i$ and finally r is given by:

$$r = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(t_i - \bar{t})}{\sum_{i=1}^{N}(t_i - \bar{t})^2}$$

Thus, r is the historical return calculated on the time scale used to measure t_i. Unless the above calculation has not be performed in "years", the result r has to be scaled in order to get an annualized rate of return.

The Coherent Market Portfolio

Definition

In the "Modern Portfolio Theory" section, the classical market portfolio was presented, which can now be improved with regard to:

1. The risk measurement was performed using the standard derivation. In the "Coherent Measures of Risk" section, it explained that a risk measure should be coherent and therefore, the standard derivation should be replaced by the expected shortfall. To assign the deterministic investment a risk of 0, any risk measurement should be performed using the deterministic investment as benchmark.
2. In classical portfolio theory, it is assumed that the returns of the securities are known and are generally greater than the risk-free interest rate. However, the returns of the securities may also be negative; as you know, there are also downward trends! The technical analysis provides concrete methods for estimating returns, and two simple approaches have been provided in the "A Trend Following Approach to Estimate Future Returns" section.

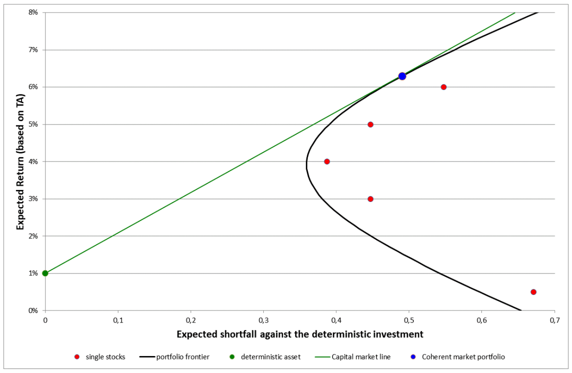
If these two adaptations are transferred to the classical definition of the market portfolio, a very similar picture to Figure 2 appears at first glance. Again, the capital market line is a straight line, as a mixture between the deterministic investment P_0 with yield r_0, and any other portfolio P_{any} with return r_{any} is linear again in the mixing ratio ω:

$$\textit{Expected Return}\left[\omega P_{any} + (1-\omega)P_0\right] = \omega r_{any} + (1-\omega) r_0 = r_0 + \omega(r_{any} - r_0)$$

$$ES\left[\omega P_{any} + (1-\omega)P_0\right] = ES\left[\omega P_{any}\right] = \omega\, ES\left[P_{any}\right]$$

In this calculation, it was assumed that the expected shortfall was computed against the benchmark P_0, the deterministic investment.

Figure 3. The coherent market portfolio



Taking a closer look at this figure, the differences from Figure 2 of the Modern Portfolio Theory become clear:

- The deterministic investment P_0 not only determines the deterministic rate r_0 but also serves as a benchmark for the risk measurement. Therefore, the P_0 is again risk-free like in the Modern Portfolio Theory.
- The assessment of risk is performed using a coherent measure of risk, namely using the expected shortfall.
- To determine the expected returns of the securities, a method based on technical analysis is applied.
- The coherent market portfolio $P_{coherent}$ is characterized by maximizing the ratio of expected excess return and risk; hence, for all portfolios, P holds:

$$\frac{\textit{ExpectedReturn}\left[P_{coherent}\right] - r_0}{ES\left[P_{coherent}\right]} \geq \frac{\textit{ExpectedReturn}[P] - r_0}{ES[P]}$$

- There is no restriction on the expected returns of a stock: It can be smaller than r_0 and could also become negative.

The last point leads to another difference to the classical market portfolio, especially in the case that short selling is allowed: If no shares have returns above the interest rate of the deterministic investment, the return of the coherent market portfolio would be less than r_0. However, such an investment makes no sense at all: Less income but more risk than the deterministic investment! In such an environment (e.g., in a classical bear market), the deterministic investment is preferable to an equity investment. The coherent market portfolio will not exist in such a situation if short selling is prohibited.

On the Uniqueness of the Coherent Market Portfolio

In Figure 3, the portfolio frontier is represented in the usual form of the Modern Portfolio Theory (black line). Against the background of the more complex risk calculation, however, a closed formula for this line is no longer given. Therefore, the question arises whether the graph is still appropriate and whether the coherent market portfolio is as well defined as it is shown in the figure.[6] To answer this question, it will be shown below that the frontier line is still convex if the risk is measured by the expected shortfall or any other coherent measure of risk. Since the coherent market portfolio is the result of a linear optimization on the convex set of achievable portfolios, the coherent market portfolio is unique.

To show that the set of achievable portfolios is convex, it is sufficient to show that the connection line between two arbitrary portfolios, P_1 and P_2, is completely contained in the set of achievable portfolios. Let $0 \leq \omega \leq 1$ denote the expected return of the portfolios P_1 and P_2 by r_1 and r_2, and define $P(\omega) = \omega P_1 + (1-\omega) P_2$. Then, for the expected return and the risk of the portfolio $P(\omega)$, measured either by expected shortfall or any coherent measure of risk, the following equations hold:

$$\textit{Expected Return}\ [P\ (\omega)] = \omega\, r_1 + (1-\omega)\, r_2$$

$$\textit{Risk}\,[P\ (\omega)] \leq \omega\ \textit{Risk}\left[P_1\right] + (1-\omega)\ \ \textit{Risk}\left[P_1\right]$$

Hence, the risk of the portfolio $P\omega$ is either smaller than the sum of the risk of the sub-portfolios or—in the case that equality holds in the last equation—it lies on the connecting line of the two portfolios. Since its risk is never greater, the connecting line is completely contained in the set of achievable portfolios, and so the portfolio frontier is convex.

How to Determine the Coherent Market Portfolio

To determine the coherent market portfolio, one must rely on numerical methods since the more complex risk calculation prevents any closed form solution for the portfolio frontier or the optimal portfolio weights. The good news is that the coherent market portfolio is the result of linear optimization on a complex set, and hence, even simple numerical algorithms will find the solution.

Consider a universe of N stocks together with a short-selling restriction, then a portfolio can be described by weights $\omega_i \geq 0$, which represent the fraction of the portfolio to be invested in the i_{th} stock. Hence, there is the restriction

$$\sum_{i=1}^{N} \omega_i = 1$$

Let denote r_i denote the expected return of the i^{th} stock, then the expected return of the portfolio is given by

$$\textit{Expected Return} = \sum_{i=1}^{N} \omega_i\, r_i$$

To determine the expected shortfall, the single loss scenarios can also be easily computed by

$$L_j = \sum_{i=1}^{N} \omega_i \left(1 - exp\left(\delta_j^i\right)\right)$$

Computing the expected shortfall requires a sorting of the losses L_j, and hence, the risk has to be computed for each portfolio composition.

A simple algorithm to determine the portfolio weights of the coherent market starts with any portfolio composition and then varies this composition gradually. In such a variation, a small fraction (e.g., 1%) of the portfolio weight is taken away from the i^{th} stock, provided it has such a high weight, and instead increases the weight of the stock J^{th}. This variation is performed for each combination of i and j, hence at most $N(N-1)$ combinations. For each of these combinations, the following ratio will be determined:

$$\frac{\textit{Expected Return}\ (\omega) - r_0}{ES(\omega)}$$

The combination, which yields to the largest ratio, is the first modification step of the portfolio, and the next iteration starts. Such successive optimization of the portfolio is performed until no improvement of the ratio can be achieved any more by a small change in the portfolio composition, and hence, the coherent market portfolio is obtained.

A Trading System Based on the Coherent Market Portfolio

Introduction of the Trading System

To complete the so far theoretical work, its practical use is now demonstrated. For this purpose, an ETF investment is considered in the European market on the one hand, and on the other hand, in the American stock market. Since a portfolio analysis is far too complex on all equities in the relevant market, the investment universe chosen are the ETFs of the sector subdivisions commonly used in the relevant market, and the interest rate for the deterministic investment is given by the deposit rate of the responsible central bank.

To ensure that the coherent market portfolio is truly composed of multiple positions, it is assumed that at least half of the sector ETFs have a return expectation above the central bank's interest rate. If this is not the case, the investment is made at the central bank interest rate. However, if there is a sufficient market breadth, the coherent market portfolio will be determined and investment will be made precisely in this coherent market portfolio. In order to keep the costs for the reallocations low, the analysis is carried out on the first weekend of each month and the portfolio changeover will take place at the opening on the following Monday.

Results of the Backtesting

Backtesting in the European Stock Market

The European market is subdivided into the 19 sectors[7] listed in Table 2, and there is an *iShares STOXX Europe 600 ETF* for each sector available and used in the backtest. The chosen market benchmark is hence given by the *iShares STOXX Europe 600 ETF*, and the interest rate for the deterministic investment is given by the deposit facility of the European Central Bank. If an ETF was launched during the backtest phase, it was considered for investment past one year after its launch date.

Table 2. The Industry Sectors in the European Market

Automobiles & Parts	**Industrial Goods & Services**	**Technology**
Banks	Insurance	Telecommunications
Chemicals	Media	Travel & Leisure
Construction & Materials	Oil & Gas	Utilities
Financial Services	Personal & Household Goods	Basic Resources
Food & Beverage	Retail	Real Estate Cap
Health Care		

Figures 4 and 5 show the equity curve of the **buy-and-hold approach** and the **investment in the coherent market portfolio** subject to the condition of a sufficient market breadth according to the described strategy. The advantage is obvious: there is a larger yield with less drawdown. Of course, the method to estimate the ETF returns has an impact on the results, but the benefit is independent of the chosen estimation method (rate-of-change or linear regression). The figures also show the phases in which the coherent market portfolio-based strategy is only invested in the money market. The numerical results of the backtest are listed in Table 3.

Figure 4. Backtest in the European Market Using the Rate of Change

Figure 5. Backtest in the European Market Using the Linear Regression

Table 3. Key Figures of the Backtest in the European Market

		Coherent Market Portfolio Strategy	
	Buy and Hold	**Using Rate of Change**	**Using Linear Regression**
Period	January 2004 to December 2018		
Seed Capital	100,000 EUR		
Final Capital	141,945 EUR	171,735 EUR	242,975 EUR
Maximum Drawdown	60.8%	28.0%	27.3%

Backtesting in the American Stock Market

The usual sector division in the U.S, market is less granular,[8] and the ETFs used for the backtest are listed in Table 4.

Table 4. The ETFs Used in the Backtest of the American Market

S&P 500 Communication Sector SPDR	S&P 500 Industrial Sector SPDR
S&P 500 Cons Staples Sector SPDR	S&P 500 Info Tech Sector SPDR
S&P 500 Consumer Disc Sector SPDR	S&P 500 Materials Sector SPDR
S&P 500 Energy Sector SPDR	S&P 500 Real Estate Sector SPDR
S&P 500 Financials Sector SPDR	S&P 500 Utilities Sector SPDR
S&P 500 Healthcare Sector SPDR	

The benchmark used in this market is the *S&P 500 SPDR*, and the interest rate for the deterministic investment is the Federal Funds Effective Rate. As before, Figure 6 and Figure 7 show the equity curve of this backtest. Again, the **buy-and-hold approach** looks worse than the equity curve of the **investment in the coherent market portfolio**, with respect to total return in terms of the maximum drawdown. The numerical results are listed in Table 5. Again, the strategy based on the Linear Regression outperforms the strategy using the more primitive estimation approach based on the Rate-of-Change.

Figure 6. Backtest in the American Market Using the Rate of Change

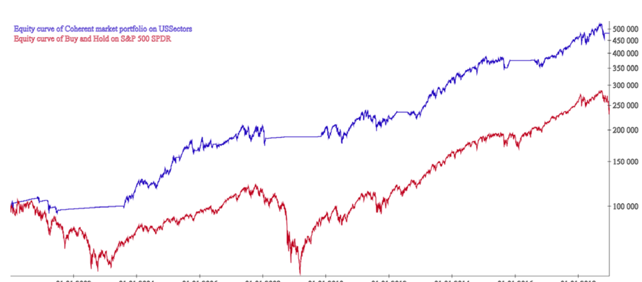


Figure 7. Backtest in the American Market Using the Linear Regression

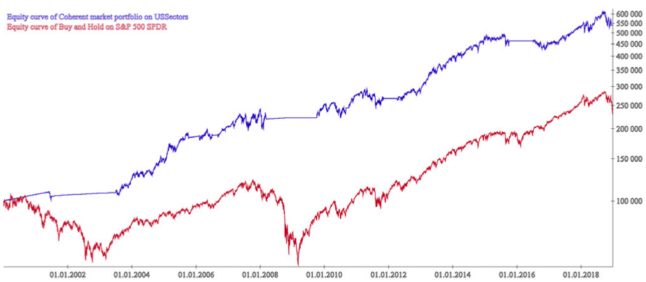


Table 5. Key Figures of the Backtest in the American Market

		Coherent Market Portfolio Strategy	
	Buy and Hold	Using Rate of Change	Using Linear Regression
Period	January 2000 to December 2018		
Seed Capital	100,000 USD		
Final Capital	243,197 USD	480,784 USD	539,120 USD
Maximum Drawdown	55.2%	17.4%	17.2%

Conclusion

"Don't Put All Your Eggs in One Basket" is the classical investment advice to draw attention to diversification as part of an investment approach. The theoretical basis for the benefits of diversification was established by Harry Markowitz and William Sharpe in their Modern Portfolio Theory. Despite the great importance of their work in economics, two criticisms of their work are often cited: On the one hand, they do cover the issue of estimating the returns of the stocks in a portfolio and, on the other hand, they use the standard deviation to measure risk. Recent research has introduced a new notion of coherent risk measures, and the estimation of stock returns is a core application of technical analysis. In the present work solutions for the criticisms of the Modern Portfolio Theory were presented and subjected to a first practical test.

To estimate the asset returns, two quite simple approaches have been used in this paper. In spite of their simplicity, both approaches were advantageous, and that alone verifies the famous statement, "The trend is your friend"! In both markets, the backtests showed that the estimation of the returns using the Linear Regression is superior to the more primitive estimation based on the Rate-of-Change. This reinforces the assumption that better estimation methods from technical analysis can yield even better results here.

From the perspective of risk, the presented strategy based on the coherent market portfolio also convinces: The maximum drawdowns of the strategies are well below the drawdown of a buy-and-hold approach.

In summary, coherent risk measurement and an estimate of stock returns using technical analysis provides the necessary building blocks for updating the Modern Portfolio Theory. Hence, a coherent market portfolio is defined that concretizes the introductory phrase since it provides a procedure that determines exactly how much to invest in which stock (i.e., "How many eggs should be put in which basket?")

Market Data

The price data for ETFs in the European market were obtained through the software TAI-PAN from the provider Lenz+Partner GmbH (www.lp-software.de), which is part of the vwd group (www.vwd.com). The price data for the U.S. Sector ETFs were obtained through finance.yahoo.com from Verizon Media and the deposit rates from the websites of the respective central banks (www.ecb.europa.eu, www.federalreserve.gov).

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Notes

1 Commonly, an investment with a fixed income in advance is called a "safe" or "risk- free" investment. This terminology is appropriate when using the standard deviation as a measure of risk. As other risk measures are considered in this paper, such investment will be called "deterministic."

2 In the following, scalar quantities are printed in normal font, vectors and matrices in boldface.

3 To favor a simpler representation, no integrability conditions are considered for $\mathcal{L}$, and hence, ρ may also take the value $+\infty$ according to this definition.

4 The term "translation invariance" is linguistically misleading since the translation has an effect on the right-hand side of the equation. Therefore, "translation compliant" would be more appropriate, but the misleading expression became standard in the context of coherent measures of risk.

5 Here, one can obtain the advantage of the logarithmic scale. Using the classical definition of relative changes, one has to consider that a share price falling from $100 USD to $80 USD is a relative move of -20%, while the counter movement from $80 USD to $100 USD corresponds to a relative gain of 25%. Using the logarithmic scale, only the sign of changes.

6 I would like to thank the jury of the VTAD award, who raised this question.

7 The definition of the European sectors are in line with the 19 Supersectors of the Industry Classification Benchmark (ICB ®) by FTSE Russell.

8 In the United States, the usual sector definition is in line with the 11 sectors of the Global Industry Classification Standard (GICS ®) by MSCI.

Antifragile Asset Allocation Model

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Abstract

Most of the active investment strategies focus on the constant excess returns generated over time through a dynamic management of positions on the market. These positions are subject to possible "black swans," events that are by definition unpredictable, destructive and only explainable afterwards. The conventional approach to risk management is to diversify investments across asset classes; however, the crashes of 2001 (dot com bubble) and 2008 (global financial crisis) questioned those portfolios that so far had been considered well diversified. The risk of such events occurring is called "tail risk." Over the last few years, many tail risk protection strategies have spread, often producing unsatisfactory results. This paper aims to demonstrate how the combination of an active quantitative investment model and an effective tail risk hedging strategy leads to the creation of an antifragile portfolio, immune to the black swans and able to exploit them to its advantage.

Introduction

In the financial world, the black swan concept has found a considerable diffusion thanks to Taleb's (2007) literary book and *New York Times* bestseller *The Black Swan,* in combination with the turbulences in financial markets.

There are three main factors that describe a black swan event:

- Rational explanations are given after a black swan event occurs. This is based on the fact that humans are able to explain and justify unexpected phenomena after it occurred.
- A black swan event always has an extreme impact: The global financial crisis had an extreme and destructive impact on the financial markets.
- A black swan event is unexpected and is deemed "improbable." It is impossible to predict a black swan event ahead of time because it is unthinkable for most of the people until it happens.

The main issue of black swans is the inability for investors to predict such extremes events (tail risk events) and correctly incorporate their impact into portfolios; they try to apply financial models based on known probabilities instead of actually taking into account their unpredictability. Financial disasters are therefore very similar to natural disasters. Earthquakes, for example, are considered to be random events, accidental and unpredictable. The occurrence of seismic events on the earth's surface is a certainty, the uncertainty concerns where they will occur, when and to what extent.

Figure 1. Relative annual energy release from earthquakes, magnitude 6 or greater, from 1900 to 2010. ***Source: U.S Geological Survey, http://www.johnstonsarchive.net/***

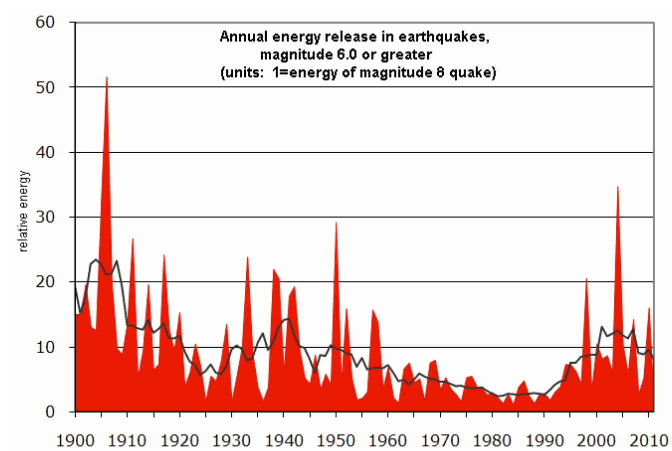
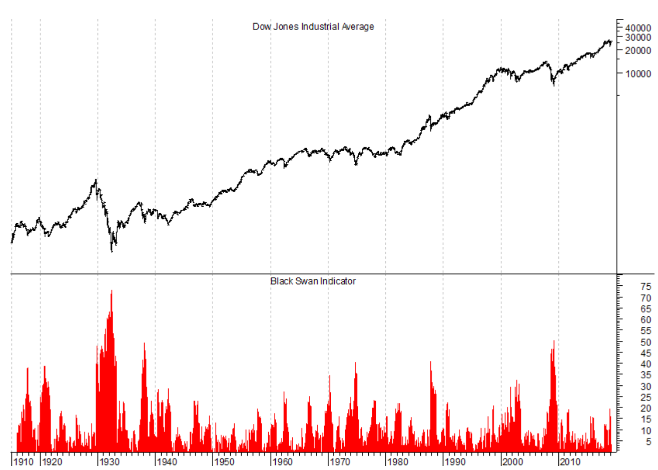


Figure 2. Dow Jones Industrial Average (black). Black swan indicator (red) shows the market corrections. Monthly data, from February 1915 to February 2019.



Through the use of historical data and statistical models it is possible to identify areas of higher seismic risk, the same way as in the financial markets it is possible to identify the riskiest asset classes based on volatility.

Figure 3. Areas across the United States that are most likely to experience a significant earthquake in the next 50 years. *Source: U.S. Geological Survey.*

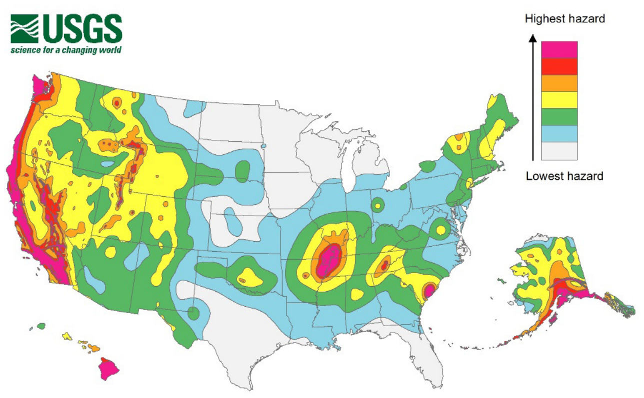


Table 1. Asset classes average annual return and standard deviation, from 1926 to 2011. *Source: BofA Merrill Lunch, Ibbotson.*

Asset Class	Avg. Annual Return (1926-2011)	Standard Deviation
Large Stocks	11.80%	20.30%
Small Stocks	16.50%	32.50%
Corporate Bonds	6.40%	8.40%
Long-Term Government Bonds	6.10%	9.80%
Intermediate Government Bonds	5.50%	5.70%
U.S T-Bills	3.60%	3.10%

The unpredictability of earthquakes, however, has not prevented humanity from building houses, selecting the most suitable land and the best technologies to make the building as resistant and flexible as possible to seismic events. The rarity, inexplicability and uncertainty of black swans makes our investment management models and, consequently, our portfolios fragile. The best antidote against fragility is antifragility, a system that can take advantage of randomness and chaos. This paper aims to demonstrate how merging the Sector Rotation Model, a sector rotation quantitative strategy, and the Black Swan Hedging Model, a tail risk hedging strategy, leads to a model capable of producing excess returns and outperformance during both positive market phases and extremely negative events. I named such model the Antifragile Asset Allocation Model.

Background and Methodology

This paper considers the studies of different authors, providing a link between different concepts and methods through personal implementation. It is worth mentioning the most influential authors, with reference to their contribution:

- Nassim Nicholas Taleb, for his contribution in defining the concept of black swans, indicating how to manage them through antifragility.
- Wouter J. Keller and Hugo S. van Putten, for their contribution to the definition of a new quantitative strategy, the Flexible Asset Allocation.
- Meb Faber, for his research on quantitative analysis and nondiscretionary strategies.
- Welles Wilder, for technical studies on breakout, range and trend concept models.
- Robert Engle and Tim Bollerslev, for the development of analytical methods of economic historical series with dynamic volatility over time.
- Martin J. Pring, for the works on the stages of the economic cycle and their definition.

The paper consists of four parts. The first part covers the Sector Rotation Model, managed by a ranking algorithm that selects the best sectors. The main quantitative factors of the ranking system are explained, and the calculation details are shown. The second part explains how some tail risk hedging strategies work and how they can be improved through a more adaptive strategy such as the Black Swan Hedging Model. The third part shows the Antifragile Asset Allocation Model, obtained by merging the models mentioned above. The final part illustrates the results of model backtesting, represented through monthly performances from June 2004 to February 2019.

Sector Rotation Model

Sector rotation consists of shifting investment assets from one sector of the economy to another to capture returns from different market cycles. Sector rotation strategies are popular because they provide diversification and risk-adjusted returns over time.

The Sector Rotation Model consists of 11 sectors of the S&P 500, represented by their respective ETFs.

Table 2. Sector Rotation Model: list of ETFs.

1	SPDR Consumer Discretionary ETF	XLY
2	SPDR Health Care ETF	XLV
3	SPDR Utilities ETF	XLU
4	SPDR Consumer Staples ETF	XLP
5	SPDR Technology ETF	XLK
6	SPDR Industrial ETF	XLI
7	SPDR Financial ETF	XLF
8	SPDR Energy ETF	XLE
9	SPDR Materials ETF	XLB
10	Vanguard Communication Services ETF	VOX
11	SPDR Dow Jones REIT ETF	RWR

The Sector Rotation Model is the main pillar of the Antifragile Asset Allocation Model because of its ability to adapt to market cycles (Recession, Early Recover, Late Recovery, Early Recession), providing the portfolio flexibility and robustness. Each month, the Sector Rotation Model ranks the 11 ETFs based on the following factors:

- (M) Absolute Momentum—to determine assets' profitability. Calculation: 4 months momentum (ROC – Rate of Change).
- (V) Volatility Model—to determine assets' risk. Calculation: edited version of GARCH Model.
- (C) Average Relative Correlations—to achieve diversification. Calculation: 4 months average correlation across the ETFs.

- (T) ATR Trend/Breakout System—to determine assets' directionality. Calculation: ATR Bands on daily timeframe. Upper Band = 42 periods ATR + Highest Close of 63 periods. Lower Band = 42 periods ATR + Highest Low of 105 periods.

$$TRANK=(wM*Rank(M)+wV*Rank(V)+wC*Rank(C)-wT*T)+M/n \quad (1)$$

Where:

Rank(M) = ranking from 1 to 11 of the assets based on the Absolute Momentum.

Rank(V) = ranking from 1 to 11 of the assets based on the Volatility Model

Rank(C) = ranking from 1 to 11 of the assets based on the Average Relative Correlation

T = ATR Trend/Breakout System

wM = % weight assigned to for ***Rank(M)*** evaluation

wV = % weight assigned to for ***Rank(V)*** evaluation

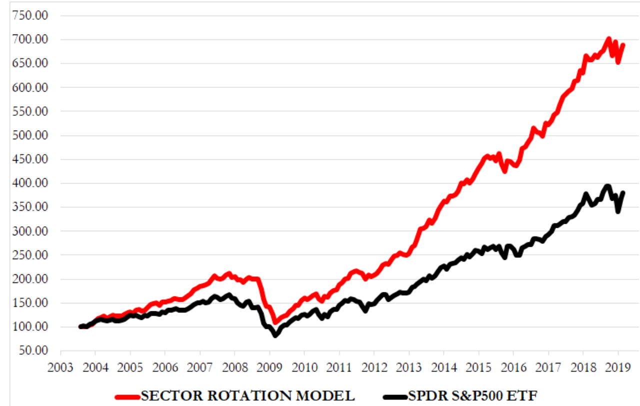
wC = % weight assigned to for ***Rank(C)*** evaluation

wT = % weight assigned to for ***Rank(T)*** evaluation

n = number of assets

The best five ETFs are selected based on each TRank and are equally weighted in the portfolio.

Figure 5. Sector Rotation Model (red) and SPDR S&P 500 (black), performance comparison. Monthly data from August 2003 to February 2019.



The Rotation Sector Model beats the S&P 500 index over time, constantly outperforming it. The model demonstrates flexibility, adapting to different market cycles, and robustness, showing resilience to medium market corrections. However, the model is not immune to crashes and black swans, so it needs a dedicated protection against such events.

Black Swan Hedging Strategy

In statistics "tails" are defined as the extremes of a distribution—the outcomes that have a small probability of occurring. In finance, tail risk represents the loss at the most negative part of an asset or portfolio's return distribution caused by infrequent and outsized downside market moves. Many studies show that equity market returns do not follow a normal distribution, with tails fatter than predicted. The traditional approach to managing portfolio risk involves investment diversification amongst not correlated assets classes: if the correlation amongst assets is low, this will mitigate the impact of big market corrections on the portfolio; however, extreme losses occur during times of crisis or financial market distress, characterized by a contagion effect and a

Table 3. Sector Rotation Model, historical returns. Monthly data from August 2003 to February 2019.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2003								1.61%	-0.31%	2.68%	1.82%	7.12%	**13.44%**
2004	3.33%	2.65%	1.87%	-3.49%	2.43%	3.44%	-1.61%	0.03%	0.40%	1.81%	2.85%	1.65%	**16.22%**
2005	-2.86%	5.81%	0.33%	-1.49%	1.27%	3.49%	4.50%	1.13%	0.95%	-2.58%	4.35%	-0.54%	**14.87%**
2006	1.35%	1.92%	1.49%	0.66%	-1.85%	0.69%	1.91%	2.90%	2.69%	4.27%	2.37%	1.42%	**21.59%**
2007	1.63%	0.65%	1.30%	4.24%	3.96%	-2.48%	-0.65%	1.15%	3.17%	1.84%	-4.22%	1.01%	**11.87%**
2008	-3.44%	-0.41%	-2.54%	4.11%	1.13%	-1.32%	0.19%	-0.63%	-10.17%	-12.53%	-8.20%	-1.86%	**-31.37%**
2009	-9.95%	-13.55%	4.19%	4.45%	2.16%	2.24%	6.51%	4.13%	5.05%	-0.58%	7.18%	3.58%	**13.80%**
2010	-2.48%	2.15%	3.73%	1.99%	-5.89%	-4.00%	7.15%	-1.18%	5.16%	3.15%	0.87%	5.73%	**16.63%**
2011	3.42%	3.59%	0.77%	4.84%	1.84%	0.80%	-1.60%	-1.11%	-5.27%	3.53%	-1.14%	1.14%	**10.88%**
2012	1.99%	4.04%	3.63%	1.87%	-0.67%	4.26%	2.63%	0.86%	1.95%	-1.12%	-0.65%	0.92%	**21.38%**
2013	5.51%	1.63%	4.75%	7.26%	0.77%	1.01%	4.68%	-2.13%	3.10%	5.04%	2.49%	2.87%	**43.46%**
2014	-0.22%	3.05%	0.11%	1.16%	1.84%	4.17%	-0.32%	2.00%	-1.71%	2.45%	2.25%	3.03%	**19.13%**
2015	2.28%	2.31%	1.43%	-1.37%	0.81%	-1.88%	3.34%	-4.88%	-3.17%	5.20%	-0.66%	-1.50%	**1.46%**
2016	-0.32%	2.65%	5.63%	0.72%	1.53%	2.41%	4.09%	-1.60%	-0.62%	-1.24%	5.59%	-0.65%	**19.38%**
2017	1.47%	2.49%	0.93%	2.58%	3.19%	0.82%	1.06%	0.88%	2.75%	0.26%	3.36%	-0.96%	**20.44%**
2018	5.84%	-1.26%	0.06%	1.46%	-0.72%	1.58%	0.39%	2.32%	1.42%	-5.07%	4.42%	-6.14%	**3.70%**
2019	3.88%	1.63%											**5.57%**

Figure 6. Sector Rotation Model, allocation across time. Monthly data from August 2003 to February 2019.

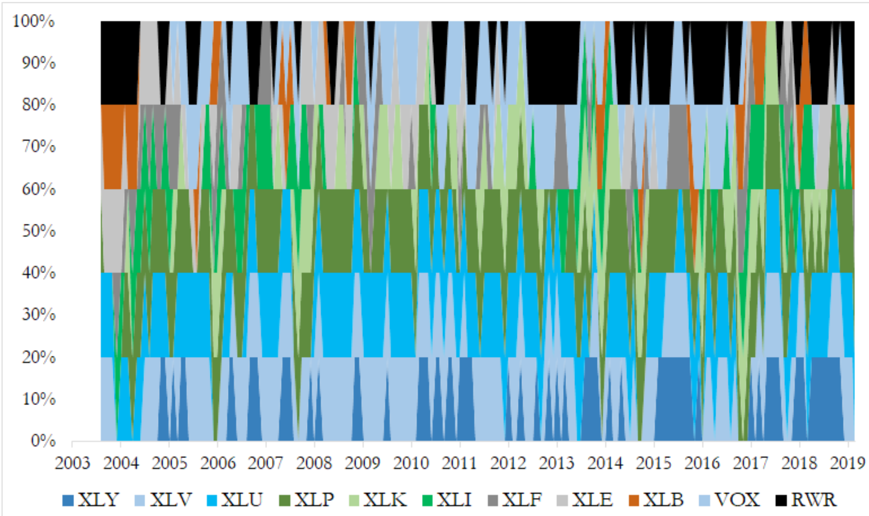


Figure 7. Hypothetical cumulative growth of $100 into 1-Year OTM Puts on the S&P. Monthly data from 1996 to 2012. ***Source: AQR***

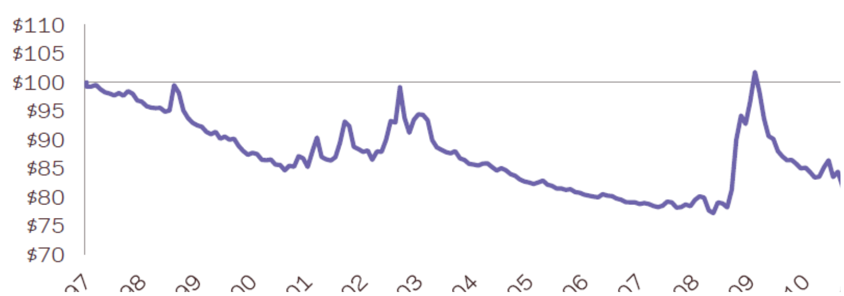


Table 4. Tail Risk strategy and S&P 500 performance comparison. From June 1986 to December 2012. ***Source: Meb Faber/GFD***

	S&P 500	80% S&P 20% TAIL RISK	60% S&P 40% TAIL RISK	40% S&P 60% TAIL RISK	20% S&P 80% TAIL RISK	TAIL RISK
Return	9.89%	8.74%	7.39%	5.86%	4.16%	2.31%
Volatility	15.11%	11.36%	8.18%	6.49%	7.38%	10.19%
Sharpe Ratio	0.44	0.48	0.50	0.39	0.12	(0.10)
MaxDD	(50.95%)	(38.20%)	(22.96%)	(10.28%)	(14.40%)	(26.64%)

Table 5. Black Swan Hedging Model: list of ETFs.

1	Invesco CurrencyShares Swiss Franc ETF	FXY
2	Invesco CurrencyShares Japanese Yen ETF	FXF
3	SPDR Gold Shares ETF	GLD
4	iShares 7-10 Year Treasury Bond ETF	IEF
5	ProShares Short S&P500 ETF	SH
6	iShares 20+ Year Treasury Bond ETF	TLT
7	iShares 1-3 Year Treasury Bond ETF	SHY

pronounced rise in many asset classes correlations to equities.

Recent market turmoils have highlighted that extreme market moves occur more frequently than most statistical models predict, and diversification strategies typically break down in these circumstances. The infamous black swans of the first two decades of the 21st century generated attention and investment flows aimed to hedge against tail risk. Theoretically, a tail risk strategy acts as a sort of insurance since it has a low or negative required rate of return, but it pays off at times of market distress. There are several tail risk hedging strategies (Puts, Delta-hedged options, volatility products), but there is significant disagreement regarding the efficacy of such strategies and their cost/benefit tradeoffs.

Table 4 represents how adding a permanent tail risk strategy that buys monthly 5% out of the money options on the S&P 500 with 90% of allocation invested in 10-year U.S. government bonds affects portfolio returns.

In all cases, the tail risk strategy brings a decrease in drawdowns, but the reduction in volatility does not compensate for the reduction in returns, so the Sharpe Ratio worsens. According to the writer's opinion, the current tail risk strategies are too static and unable to adapt to different types of market corrections.

The Black Swan Hedging Model, hereby explained, consists of seven ETFs representing different types of asset classes that can benefit from market corrections of a different nature.

The best three ETFs will be considered for the upcoming allocation, based on the ranking system described in the prior paragraph. For each of the three ETFs, if it has a positive Absolute Momentum (M), then it will be included in the portfolio; otherwise, its weighting will be replaced with cash, represented by iShares 1-3 Year Treasury Bond ETF.

In an extreme case where all the top three ETFs have a negative Absolute Momentum (M), cash will assume a 100% weighting.

The Black Swan Hedging Model provides effective protection against market corrections, demonstrating the ability to take advantage of the most extreme events.

Antifragility

The Antifragile Asset Allocation Model represents the union between the Sector Rotation Model and the Black Swan Hedging Model. The Sector Rotation Model selects the five best sector ETFs.

For each of the five ETFs, if it has a positive Absolute Momentum (M), then it will be included in the Antifragile Portfolio with a 20% weighting. If all the top five sector ETFs have a negative Absolute Momentum (M), the Black Swan Hedging Model allocation will assume a 100% weighting.

The unassigned weighting will be replaced with the Black Swan Hedging Model allocation.

The Antifragile Asset Allocation Model maintains the qualities of the strategies from which it derives, showing adaptability to different market cycles, resilience against market corrections, and antifragility against extreme events.

Application and Empirical Tests

The Antifragile Asset Allocation Model works by applying the algorithms discussed in the previous paragraphs. The database is end-of-day and it is downloaded from Yahoo! Finance. Where

Figure 8. Black Swan Hedging Model (red) and SPDR S&P 500 (black), performance comparison. Monthly data from August 2003 to February 2019.

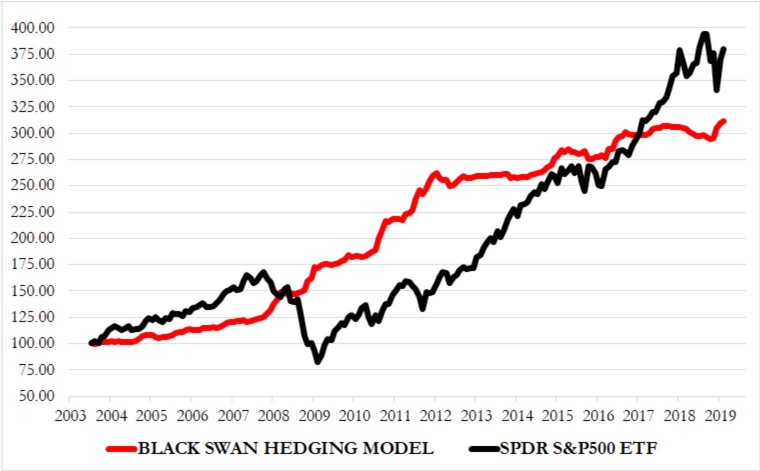


Figure 9. Black Swan Hedging Model, allocation across time. Monthly data from August 2003 to February 2019.

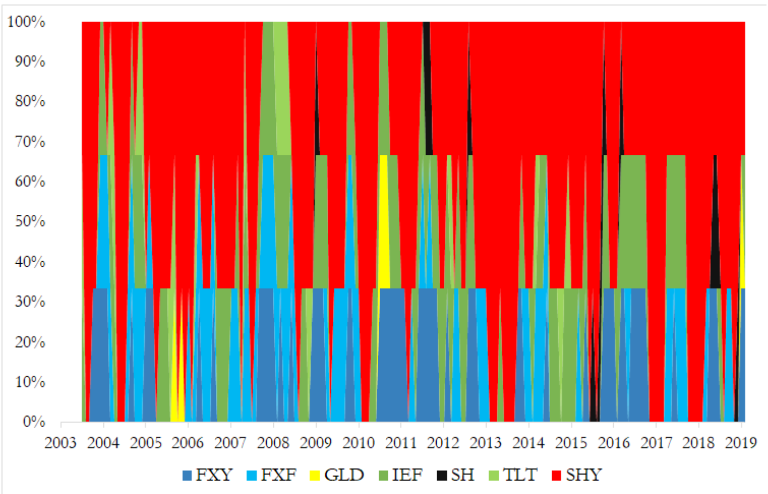


Table 6. Black Swan Hedging Model, historical returns. Monthly data from August 2003 to February 2019.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2003								-0.05%	0.95%	0.13%	-0.01%	0.72%	**1.74%**
2004	0.99%	-1.14%	0.57%	-1.16%	0.00%	-0.03%	0.25%	1.06%	2.17%	2.87%	0.54%	-0.28%	**5.93%**
2005	-0.13%	-1.34%	-0.80%	0.49%	0.48%	0.60%	0.82%	1.59%	1.22%	-0.09%	2.20%	0.04%	**5.15%**
2006	-0.31%	-0.27%	0.28%	1.86%	-0.03%	-0.04%	0.23%	-0.56%	0.97%	1.40%	1.54%	0.95%	**6.15%**
2007	-0.10%	0.92%	0.31%	0.28%	-0.93%	0.45%	0.89%	0.49%	0.79%	0.81%	3.44%	1.91%	**9.60%**
2008	4.35%	3.43%	4.61%	-0.72%	-0.24%	0.47%	-0.53%	0.41%	0.62%	1.33%	5.45%	1.99%	**23.06%**
2009	6.26%	-0.62%	1.90%	0.64%	0.02%	-0.62%	0.63%	0.58%	0.88%	0.55%	2.56%	-0.80%	**12.43%**
2010	0.26%	0.06%	-0.26%	0.29%	1.10%	1.17%	0.88%	5.37%	4.94%	3.42%	-0.28%	1.40%	**19.73%**
2011	-0.17%	-0.05%	-0.12%	2.41%	0.47%	1.39%	4.70%	3.43%	-1.73%	2.48%	2.93%	1.78%	**18.79%**
2012	0.95%	-1.70%	-0.92%	-0.06%	-2.14%	0.58%	1.04%	1.05%	1.15%	-0.80%	0.18%	0.39%	**-0.35%**
2013	0.23%	0.04%	0.04%	0.07%	0.33%	-0.10%	0.16%	-0.10%	0.22%	0.02%	-1.24%	0.40%	**0.05%**
2014	-0.39%	0.06%	0.03%	0.19%	0.51%	0.44%	0.31%	0.59%	0.79%	1.10%	0.53%	2.42%	**6.77%**
2015	0.66%	2.15%	-0.70%	0.92%	-0.81%	-0.06%	-0.75%	0.23%	0.81%	-2.62%	-0.12%	0.67%	**0.30%**
2016	0.25%	0.42%	-1.04%	3.15%	0.13%	2.76%	1.10%	0.27%	1.24%	-0.48%	-0.47%	0.00%	**7.50%**
2017	0.24%	-0.02%	0.06%	0.34%	1.47%	0.17%	0.05%	0.71%	0.10%	-0.09%	-0.22%	-0.13%	**2.68%**
2018	-0.08%	-0.20%	-0.28%	-1.07%	-0.47%	-0.82%	0.07%	0.34%	-0.52%	-0.83%	0.37%	3.41%	**-0.17%**
2019	1.36%	0.68%											**2.04%**

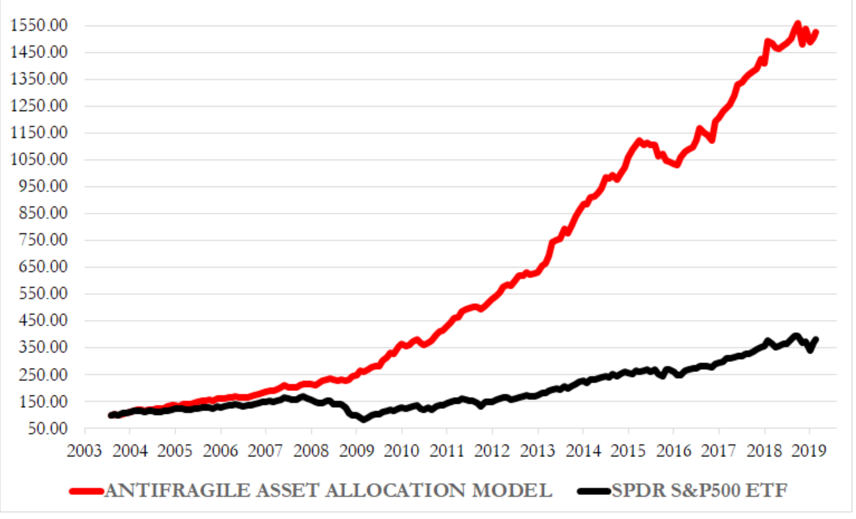
Table 7. Black Swan Hedging Model, statistics summary.

BLACK SWAN HEDGING MODEL			
Absolute Performance	211.53%	Annualized STD	4.75%
Performance YTD	2.04%	Sharpe Ratio	1.33
Worst Year	-0.35%	Max DrawDown 3m	-3.11%
Best Year	23.06%	Max Drawup 3m	13.73%
Worst Month	-2.62%	Positive Months	127
Best Month	6.26%	Negative Months	61

Table 8. Antifragile Asset Allocation Model, list of ETFs and respective weighting, updated to 02/19/2019.

ANTIFRAGILE ASSET ALLOCATION MODEL - 02/19/2019			
1	SPDR Consumer Discretionary ETF	XLY	0.00%
2	SPDR Health Care ETF	XLV	0.00%
3	SPDR Utilities ETF	XLU	20.00%
4	SPDR Consumer Staples ETF	XLP	0.00%
5	SPDR Technology ETF	XLK	0.00%
6	SPDR Industrial ETF	XLI	0.00%
7	SPDR Financial ETF	XLF	0.00%
8	SPDR Energy ETF	XLE	0.00%
9	SPDR Materials ETF	XLB	0.00%
10	Vanguard Communication Services ETF	VOX	0.00%
11	SPDR Dow Jones REIT ETF	RWR	20.00%
12	Invesco CurrencyShares Swiss Franc ETF	FXY	20.00%
13	Invesco CurrencyShares Japanese Yen ETF	FXF	0.00%
14	SPDR Gold Shares ETF	GLD	0.00%
15	iShares 7-10 Year Treasury Bond ETF	IEF	20.00%
16	ProShares Short S&P500 ETF	SH	0.00%
17	iShares 20+ Year Treasury Bond ETF	TLT	0.00%
18	iShares 1-3 Year Treasury Bond ETF	SHY	20.00%
			100.00%

Figure 10. Antifragile Asset Allocation Model (red) and SPDR S&P 500 (black), performance comparison. Monthly data from August 2003 to February 2019.



necessary, interpolations have been made with consistent historical series to achieve temporal homogeneity.

Data interpolation was performed on RStudio; Absolute Momentum, Volatility Model, Average Relative Correlation, and ATR Trend/Breakout System indicators were programmed on Metastock; classification and the rankings were programmed on Excel. The test was performed on a USD portfolio consisting mainly of ETFs to ensure maximum plausibility.

Daily and monthly returns are used. Simulation results are from August 2003 through February 2019. No transaction costs are included. All results are gross of any transaction fees, management fees, or any other fees that might be associated with executing the models in real time.

The current allocation of the portfolio is determined by the ranking model of the previous month.

The ranking model in the last session of the current month determines the allocation of the following month.

To assess the effectiveness of the proposed strategy, the performance of the Antifragile Asset Allocation Model was compared to the Salient Risk Parity Index, managed by a risk parity portfolio with 10% volatility targeting.

Conclusion

In this paper, I focused on creating an asset allocation model inspired by the concept of antifragility proposed by N.N. Taleb: capable of gaining from disorder and unpredictable events. To achieve this goal, I've created a ranking algorithm that selects the best assets over time. The algorithm consists of quantitative factors such as Momentum, Correlations, Volatility and Trend to determine, respectively, profitability, diversification, risk and directionality of the assets. To achieve antifragility, the ranking system has been applied to two models with different characteristics: Sector Rotation Model and the Black Swan Hedging Strategy. The first model beats the benchmark, represented by the SPDR S&P 500 ETF, and constantly outperforms it over time, showing adaptability to different economic cycles and robustness during medium-sized market corrections. The

Figure 11. Ranked Asset Allocation Model (red), Salient Risk Parity Index (green), performance comparison. Monthly data from January 2004 to February 2019.

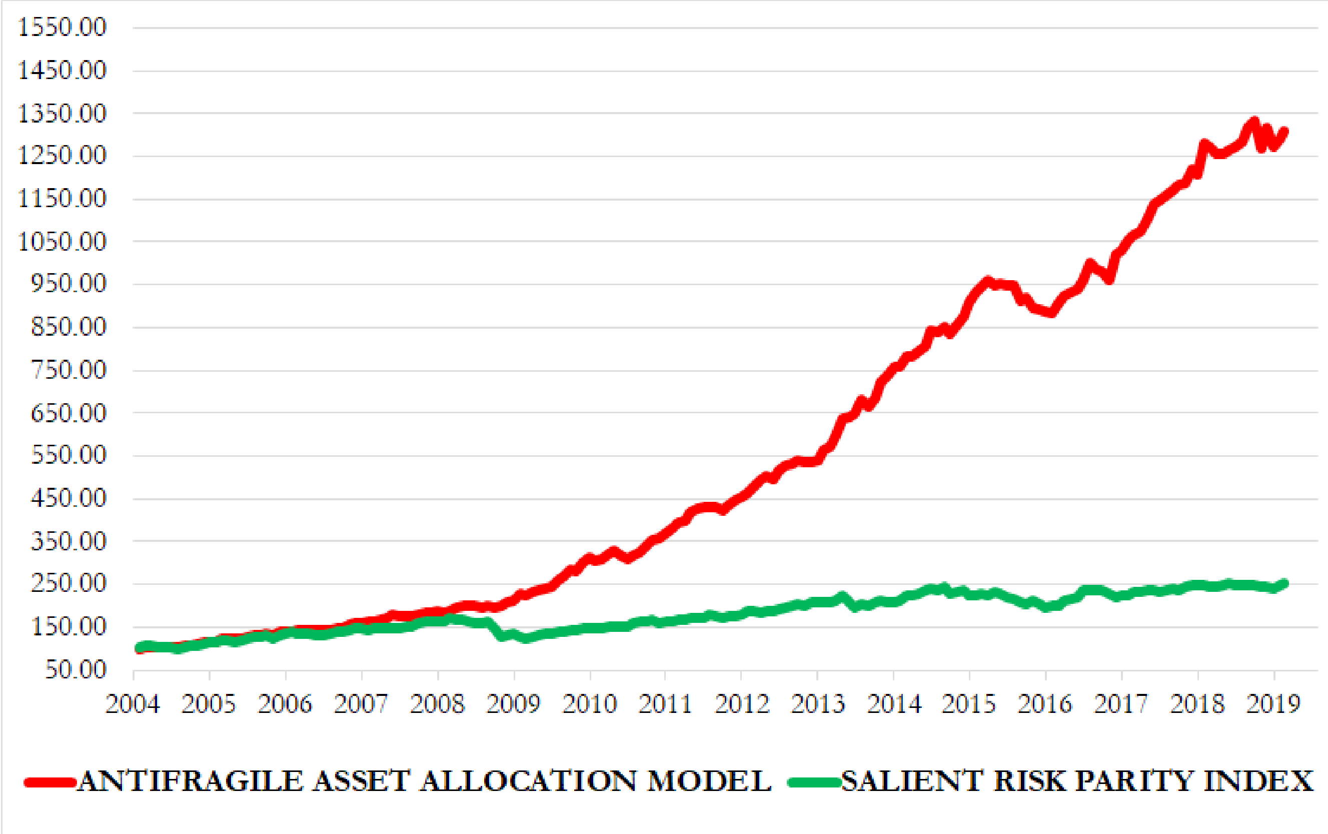


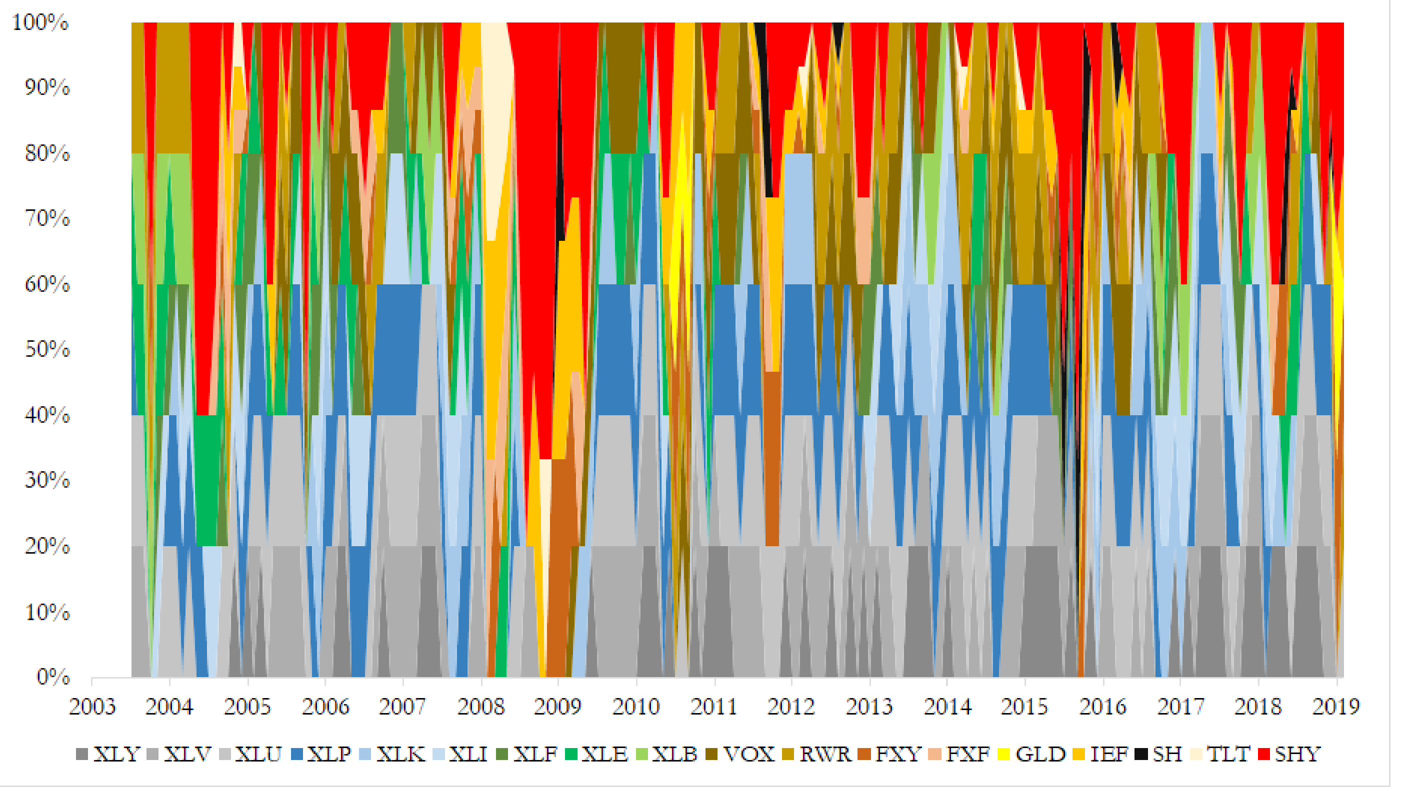
Table 9. Antifragile Asset Allocation Model, historical returns. Monthly data from August 2003 to February 2019.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
2003								1.61%	-0.31%	2.29%	1.82%	7.12%	**13.01%**
2004	3.33%	2.65%	1.87%	-3.49%	1.35%	2.20%	0.21%	0.34%	2.40%	3.82%	3.89%	0.55%	**20.63%**
2005	-1.78%	5.81%	0.33%	0.18%	0.53%	3.49%	3.56%	1.13%	0.95%	-1.52%	4.35%	-0.48%	**17.53%**
2006	1.35%	1.60%	1.49%	0.66%	-1.43%	0.75%	-0.05%	1.71%	1.65%	3.99%	2.37%	1.42%	**16.55%**
2007	1.63%	0.65%	1.30%	4.24%	3.96%	-2.48%	-0.65%	0.50%	3.30%	1.62%	-0.13%	1.73%	**16.61%**
2008	-2.50%	3.43%	4.61%	1.50%	0.84%	-0.29%	-2.09%	0.74%	-1.07%	1.33%	5.45%	1.99%	**14.49%**
2009	6.26%	-0.62%	2.97%	2.60%	1.19%	0.79%	6.51%	4.13%	5.05%	-0.58%	7.18%	3.58%	**46.31%**
2010	-2.48%	2.15%	3.19%	1.99%	-3.04%	-2.72%	2.69%	1.98%	5.85%	3.15%	0.87%	3.85%	**18.42%**
2011	3.14%	3.59%	0.77%	4.84%	1.84%	0.80%	0.06%	0.18%	-1.54%	2.71%	2.55%	1.85%	**22.71%**
2012	2.39%	2.79%	3.36%	1.87%	-1.21%	3.80%	2.63%	0.23%	1.95%	-1.12%	0.37%	0.74%	**19.15%**
2013	3.97%	1.63%	4.07%	7.26%	0.77%	1.01%	4.68%	-2.13%	3.11%	5.04%	2.49%	2.87%	**40.45%**
2014	-0.22%	3.05%	0.22%	1.47%	1.84%	4.17%	-0.32%	1.27%	-1.71%	2.45%	2.25%	3.68%	**19.53%**
2015	2.79%	1.42%	1.43%	-1.20%	0.47%	-0.52%	-0.02%	-3.65%	0.81%	-2.62%	-0.48%	-0.65%	**-2.36%**
2016	-0.32%	2.65%	2.10%	0.76%	0.74%	2.41%	4.09%	-1.60%	-0.62%	-1.79%	6.26%	0.85%	**16.34%**
2017	2.09%	1.25%	0.93%	2.58%	3.19%	0.82%	1.05%	0.88%	1.02%	0.53%	2.69%	-0.96%	**17.24%**
2018	5.84%	-0.53%	-1.32%	-0.16%	0.71%	0.75%	1.07%	2.32%	1.42%	-5.07%	3.90%	-3.22%	**5.37%**
2019	1.36%	1.27%											**2.65%**

Table 10. Antifragile Asset Allocation Model (AAAM) and Salient Risk Parity Index, statistics summary.

	PORT AAAM	Salient RP Index		PORT AAAM	Salient RP Index
Absolute Performanc	1427.25%	153.70%	Annualized STD	7.70%	9.54%
Performance YTD	2.65%	6.08%	Sharpe Ratio	2.53	0.53
Worst Year	-2.36%	-16.87%	Max DrawDown 3m	-5.45%	-22.82%
Best Year	46.31%	18.57%	Max Drawup 3m	15.69%	10.82%

Figure 12. Antifragile Asset Allocation Model: allocation across time. Monthly data from August 2003 to February 2019.



second one proves to be a valid alternative to the most popular tail risk hedging strategies, gaining during black swans while maintaining low volatility. The antifragility is achieved by merging the peculiarities of both models. The Antifragile Asset Allocation Model proves to be dynamic and flexible during the positive phases of the market, resilient and able to exploit negative events of various nature to its advantage.

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Note

Source: http://www.salientindices.com/risk-parity.html

In Memoriam

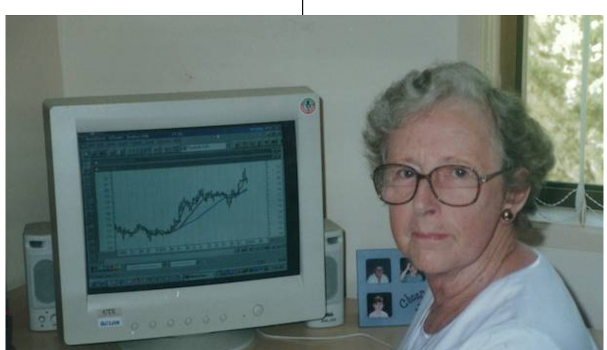
Dawn Bolton-Smith

4 April 1930—29 August 2017
Sydney, Australia

Dawn Heather Bolton-Smith (nee Dearing) was born in Earlwood, Sydney, Australia, in April 1930. April 1930 was a significant month, not only for Dawn and her family, but also for stock markets. It was the month the New York Dow Jones Index retraced to a high after the 1929 October crash. Following this event, the market then cascaded to its low in July 1932. Perhaps that is why Dawn always relished a good bear market.

At around age 19, Dawn started a career as a commercial artist, which in some ways ties in with what would become her future profession, as she brought an artistic flair to her many hand drawn charts. In fact, when once questioned by an English broker, on why she described the charts as beautiful works of art, she simply said "they certainly are to me".

In 1962 she attended a local evening college to learn technical analysis (TA). The lecturer was a young Ian Notley, who was to become one of TA's leading lights. He too must have been a fast learner, as Dawn said at the time that he was always one chapter ahead of the students.



Dawn quickly abandoned ideas for careers in art or accounting, and, armed with no more than a burning passion and the latest copy of Edwards and Magee's *Technical Analysis of Stock Trends*, she set out to establish a new career in the fledgling field of TA in Australia. In the TA world of the 1960s, training and computer-generated charts were nonexistent. A hard copy book was the source for knowledge, and if you wanted a chart of an index, or anything else, it was hand drawn.

Dawn was the first chartist employed by the Australian Stock Exchange and later helped establish the futures markets in Australia. She was also a founding member of the Australian Technical Analysts Association (ATAA), becoming a life member of that association as well as the Australian Professional Technical Analysts (APTA).

Dawn's passion for TA led to an office of wall-to-wall charts and meticulously organised folders of more and more charts. If one were to ask her about the New York Dow Jones, for instance, she would recruit the help of the nearest three people to unfurl a very long hand drawn chart holding years of history. Dawn was always willing to share her vast knowledge, and with her enthusiasm, she told many a tale (all true), including one about selling gold futures at US$840 before they opened the next day down at US$220.

In the 1960s and 1970s, Dawn worked in broking houses charting the great Australian resources boom. In 1973, she predicted the 1974 stock market crash to within four points of the bottom. After a stint working in commodities, Dawn joined the National Mutual Royal Bank in their Forex department. Her daily *Dawn Report* with her ideas for the currency moves was a fixture of that department for many years. Dawn loved working at the bank. It was during this time that she worked in London and Canada and travelled widely.

For many years, Dawn contributed a column to The *Sunday Telegraph* newspaper in Sydney and a technical analysis commentary for *The Bulletin* magazine. From 1976 to 1978, she was the editor of the trading newsletter *Trendex* and wrote a regular column for the *Iris Report* from 1994 until 2002.

Even though Dawn formerly retired from the bank in 1992, she never really retired. Her lifelong passion was TA, and every day she would be in her study following the markets. She continued to teach and write, giving lectures, corresponding with fellow practitioners around the world, and writing for the magazine *Your Trading Edge* up until April 2017. One of her favourite charting methods was the clustering of moving averages, and in her later years it featured in many of her talks. Dawn could not be without her beloved charts, and when enjoying outings such as retiree bus trips, she would take her iPhone with her to check the market and record the changes for her point and figure charts, which she continued to draw by hand.

Dawn's career spanned more than 50 years. She was a trailblazer for women in an industry that was at the time dominated by men; she was a trailblazer for TA, being the first market technician to be employed in the Australian Stock Market; and she was the first chartist to write for *The Bulletin* magazine, a woman no less. During her long career, she received many accolades and awards, all of which she took in stride with her characteristic modesty. When talking about her life's work, she simply described herself as "not just your average housewife". However, there was one accolade that she quite enjoyed, appealing to her ironic sense of humour, which was David Fuller dubbing her the "iron lady of technical analysis".

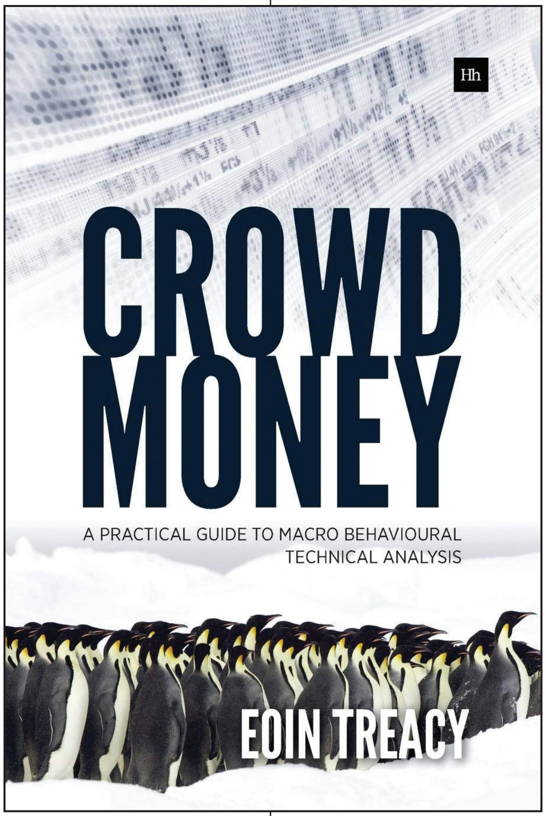
Compiled by Regina Meani from her memories of Dawn and from contributions made by Chris White, one of Dawn's lifelong friends, and Jen Hendriksen (nee Charles), who was mentored by both Dawn and David Fuller.

Crowd Money: A Practical Guide to Macro Behavioural Technical Analysis *by Eoin Treacy*

Reviewed by Regina Meani, CFTe

It was with a shiver that I read David Fuller's foreword to Crowd Money. We sadly lost David Fuller earlier this year, and while this is a review of Eoin Treacy's Crowd Money, I feel that it is also a tribute to David Fuller and his great achievements in the field of technical analysis. In Crowd Money we gain an insight into Fuller's methodology based on lifelong observation[1] in behavioural technical analysis.

Eoin Treacy has a degree in philosophy from Trinity College, Dublin and joined Fullermoney in 2003 after three years with Bloomberg teaching seminars on the interpretation of price action. At Fullermoney he specialised in Fuller's unique approach to combining technical, fundamental and behavioural analysis for their research and investment strategy.



In his introduction, Eoin Treacy tells us a basic truth that not only applies to macro behavioural technical analysis but to all forms of market analysis. He suggests that our analysis should be devoted to ensuring we learn the lessons market history is teaching us so that we can script how markets will perform in future.[2]

As I began to browse the chapters, I must confess that I quickly jumped to "Chapter 23: Themes for the Decades between 2015 and 2025," excited at the prospect of what it may hold. Here, Treacy proposes that we need to identify the motivating theme behind the market action. He addresses the broad principles from which he believes should be the major influences of market strategy through the prime driver of productivity—these being labour, population, the influence of unconventional energy production, the leaps and bounds in technology, and the use of debt. Treacy concludes that if these factors come together to increase productivity, then there could be a confluence of powerfully bullish outcomes.[3]

The early chapters treat us to Treacy's interpretation of the differences between chart reading and technical analysis. He delves into the concept of emotional intelligence and the role that fear, greed, and love play in our investment "relationships." He moves on to break down the psychological stages of major bull and bear market cycles.

Chapter 9 takes an interesting foray into consistency in trends and the mistakes we make with charts. There are three things you will see on a chart: what you want to see, what you think you will see and what is really there.[4] He terms this Triple Vision. Within this chapter, he suggests that as we progress in our analysis, we also need to ask the right questions. When we ask what the target is and where the price is going, we are asking the correct questions, but where you pose them is the real question. As he scopes the trend, Treacy believes that these should be the last questions that one asks, not the first.

Chapters 11 through 16 deal with some of the more useful technical analysis techniques, which include moving averages, trends, reversals and more behavioural practices. Following this, he discusses how we should address the significance of monetary policy, governance, and the regulatory system and how they can affect our investment strategy.

Finally, he presents us with his "Autonomies," a term coined by David Fuller to label large multinational companies, which he calls mobile principalities…they are independent, powerful, mobile 'mini countries' that focus where the best potential for profit exists[5]

Eoin Treacy has given us an amazing insight into the Fullermoney methodology in a very readable and practical guide and allows it to stand as a testament to David Fuller's legacy.

References

1 E Treacy, *Crowd Money, A Practical Guide to Macro Behavioural Technical Analysis, Harriman House, Hampshire, Great Britain, 2013, p xi*
2 ibid, p xvii
3 ibid, p 265
4 ibid, p 97
5 ibid p, 276

Author Profiles

Thomas Bulkowski

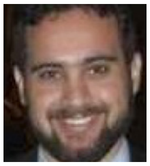
Thomas Bulkowski is a private investor and trader with almost 40 years of market experience and is considered by some to be a leading expert on chart patterns. He is the author of several books, including *Chart Patterns: After the Buy; Getting Started in Chart Patterns, Second Edition;* and the *Evolution of a Trader* trilogy. His website and blog, www.thepatternsite.com, have more than 700 articles of free information dedicated to price pattern research.

Min Deng

Min Deng has 28 years of extensive work experience in the Chinese stock markets, along with 20 years of hands-on expertise in the international financial futures markets. By relying on such experience and on the significant breakthrough achievements accomplished on the actual investor behavior and stock price behavior, he is capable of making his independent judgment on whether or not the mainstream financial investment theories are scientific in nature. His two representative research papers, titled "Death of the EMH" and "Death of the CAPM," which were accepted for presentation at leading financial conferences, successfully drew the attention of the financial academic circles and financial investment management circles worldwide.

Min had once managed two investment service companies and had been in charge of a large research project developing global financial futures trading systems involving a total cost of more than 1 million US$ spanning over 10 years. Currently, he is providing customized investment consultancy services to a large private financial investment group in China and several wealthy overseas Chinese family businesses abroad. Together with his partners, he is planning on implementing a large-scale investment education project drawing on his theoretical studies achievements and hands-on trading techniques to educate the Chinese investors in their hundreds of millions. In this regard, prior support-cum-approval is being sought from the Chinese securities administration authorities. At the same time, he is acting as the China representative of one of the biggest names in Wall Street dealing with B shares trading in the Chinese stock markets.

Akram El Sherbini, CETA, CFTe, MFTA



Akram El Sherbini, CETA, CFTe, MFTA, holds a B. Sc. in physics from the American University in Cairo. He has been involved in financial markets since 2007. Prior to freelancing, he was a technical analyst at Synergy Capital Markets and dealing desk team leader at Candle Egypt. His focus is on creating new technical indicators as well as developing unified trading systems for equity and FX markets. He is the creator of the time cycle oscillators and the performance indicators. Akram is also a member of the Egyptian Society of Technical Analysts (ESTA).

Gioele Giordano, CSTA, CFTe

Gioele Giordano, CSTA, CFTe, is a student at the University of Modena and Reggio Emilia in the Department of Economics Marco Biagi. Gioele served as a financial analyst for Market Risk Management s.r.l (MRM), a leading firm in independent financial advisory for institutional and private clients, based in Milan. As an analyst, he wrote reports on the main asset classes and developed quantitative investment models. Gioele is a member of the Italian Society of Technical Analysis (SIAT) and won the SIAT Technical Analyst Award in 2016 and the Charles H. Dow Award in 2018. He is the 2019 NAAIM Founders Award winner for his paper "Antifragile Asset Allocation Model."

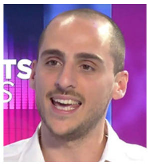
Christian Lundström, Ph.Lic.

Christian Lundström received his B.S., M.S., and Ph.Lic. degrees in economics from Umeå University, Sweden. As a researcher, he is the author of numerous peer-reviewed papers related to investing, technical trading strategies, and money management. Christian is the head of the Fund Selection and Compliance Unit at the Swedish Pensions Agency, overseeing the fund selection/due diligence work for all funds in the premium pension fund platform (one of the largest fund platforms in the world). Christian has a strong background as an investor in all major asset classes from his previous employment as fund manager at Carnegie Investment Bank, senior advisor in manager selection at Folksam, and chief investment officer at Independent Investment Group.

Regina Meani, CFTe

Regina Meani, CFTe, covered world markets as a technical analyst and associate director for Deutsche Bank prior to freelancing. She is an author in the area of technical analysis and is a sought-after presenter both internationally and locally, lecturing for various financial bodies and universities as well as the Australian Stock Exchange. Regina is a founding member and former president of the Australian Professional Technical Analysts (APTA) and a past *Journal* director for IFTA. She carries the CFTe designation and the Australian AMT (Accredited Market Technician). She has regular columns in the financial press and appears in other media forums. Her freelance work includes market analysis, webinars, and larger seminars; advising and training investors and traders in market psychology; CFD; and share trading and technical analysis. She is also a former director of the Australian Technical Analysts Association (ATAA) and has belonged to the Society of Technical Analysts, UK (STA) for over 30 years.

Alessandro Moretti, CFTe, MFTA



Alessandro Moretti, CFTe, MFTA, is an independent technical analyst in the stock market. He is the author of the book *Smart Investing: How to Invest in Stocks with Success.*

Alessandro founded the project SegnaliDiTrading.net in 2016, where he plays the role of a creator of an operative strategy, handles investment portfolios, and provides professional financial education for retail and professional clients.

In his latest paper, Alessandro presented the investment strategy based on sector rotation, which, through the combined use of relative strength and Donchian channels, allows one to beat the American stock market in the long-term perspective. His research was carried out over a period of 20 years using both sectoral indices for a theoretical study and also ETFs. With the achieved results, Alessandro had the chance to apply the strategy to his portfolios.

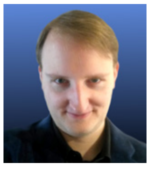
Dr. Oliver Reiss, CFTe, MFTA

Dr. Oliver Reiss, CFTe, MFTA, received a master's degree in physics from the University of Osnabrueck and a Ph.D. in mathematics from the University of Kaiserslautern—the latter for his research on financial mathematics performed at the Weierstrass Institute in Berlin. Oliver works in the banking industry and is a self-employed consultant for financial institutions, with a focus on risk control, derivatives pricing (quant), and related IT implementations.

As a private investor, Oliver was interested in technical analysis and joined the Vereinigung Technischer Analysten Deutschlands e.V. (VTAD) when he became a freelancer in 2011. Currently, Oliver serves as deputy manager of the VTAD's regional group in Dusseldorf and is a frequent attendee of the IFTA conferences. He will present his research at the IFTA conference in Cairo this year. Due to his mathematical and programming expertise, he is focused on the development and backtesting of mid-term trading strategies.

In his John Brooks Memorial Award-winning MFTA paper, Oliver presents an introduction to the Empirical Mode Decomposition (EMD), which is designed to identify cycles with changing amplitude or wavelength.

Dr. Patrick Winter



Dr. Patrick Winter lives in Germany and is an IT entrepreneur. He has earned two B.Sc. degrees and a doctoral degree in information systems and business administration, all with distinction, from the Universities of Osnabrück and Marburg. He is especially interested in methodological research, which he regularly applies to trading. For these articles, he won awards from the VTAD (Association of Technical Analysts in Germany) four times in a row. He usually does not trade himself, however, because he is convinced that it is even more efficient to create value than to trade it, especially as investors then have an incentive to work with rather than against each other.

Kersten Wöhrle, MFTA

Kersten Wöhrle, MFTA, started his career with an apprenticeship as a precision mechanic. For further career development, he focused on the growth market of medical technology and laboratory diagnostics. Therefore, he studied medical technology at the MTAE in Esslingen and earned the electronics certificates II, III, IV C and IV D in his free time while working in Munich. Over the next 30 years, he worked for two leading employers in the research and development of medical systems and laboratory diagnostic systems. In the last 10 years prior to his retirement in 2017, he worked as a product manager for coagulation systems for professional laboratory diagnostics.

For 25 years, Kersten has been intensively involved with financial market analysis in his free time. His focus and interest is the search and analysis of natural cyclical patterns that reveal a synchronicity with the financial markets. The biggest discovery so far was the 27.02 Day Cycle. Based on this cycle, the 27.02 Day Cycle model was developed. In his MFTA paper, Kersten describes the mathematical relationship of the 27.02 Day Cycle with the solar rotation period, the anomalistic period of the earth, Pi, and the fine-structure constant. Kersten uses the example of the S&P 500 to demonstrate how the emergence of emancipated cycles can be detected and calculated with the 27.02 Day Cycle as carrier frequency and natural time base.

Since 2015, Kersten has been a member of the VTAD in Frankfurt. He has since presented the 27.02 Day Cycle Model at several regional conferences. Due to the great interest, the current status since 2017 is published on the VTAD homepage with every 27.02 Day Cycle completion. This makes the 27.02 Day Cycle Model forecast transparent to all interested parties and comparable to the actual development.

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Certified Financial Technician (CFTe) Program

IFTA Certified Financial Technician (CFTe) consists of the CFTe I and CFTe II examinations. Successful completion of both examinations culminates in the award of the CFTe, an internationally recognised professional qualification in technical analysis.

Examinations

The CFTe I exam is multiple-choice, covering a wide range of technical knowledge and understanding of the principals of technical analysis; it is offered in English, French, German, Italian, Spanish, Arabic, and Chinese; it's available, year-round, at testing centers throughout the world, from IFTA's computer-based testing provider, Pearson VUE.

The CFTe II exam incorporates a number of questions that require essay-based, analysis responses. The candidate needs to demonstrate a depth of knowledge and experience in applying various methods of technical analysis. The candidate is provided with current charts covering one specific market (often an equity) to be analysed, as though for a Fund Manager.

The CFTe II is also offered in English, French, German, Italian, Spanish, Arabic, and Chinese, typically in April and October of each year.

Curriculum

The CFTe II program is designed for self-study, however, IFTA will also be happy to assist in finding qualified trainers. Local societies may offer preparatory courses to assist potential candidates. Syllabuses, Study Guides and registration are all available on the IFTA website at http://www.ifta.org/certifications/registration/.

To Register

Please visit our website at http://www.ifta.org/certifications/registration/ for registration details.

Cost

IFTA Member Colleagues	Non-Members
CFTe I $550 US	CFTe I $850 US
CFTe II $850* US	CFTe II $1,150* US

*Additional Fees (CFTe II only):
$100 US applies for non-IFTA proctored exam locations

MFTA
IFTA Master of Financial Technical Analysis

Master of Financial Technical Analysis (MFTA) Program

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Your paper must meet the following criteria:

- It must be original
- It must develop a reasoned and logical argument and lead to a sound conclusion, supported by the tests, studies and analysis contained in the paper
- The subject matter should be of practical application
- It should add to the body of knowledge in the discipline of international technical analysis

IFTA
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Timelines & Schedules

There are two MFTA sessions per year, with the following deadlines:

Session 1	
"Alternative Path" application deadline	February 28
Application, outline and fees deadline	May 2
Paper submission deadline	October 15
Session 2	
"Alternative Path" application deadline	July 31
Application, outline and fees deadline	October 2
Paper submission deadline	March 15 (of the following year)

To Register

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